HOW DID BABALATV CHANGE ONLINE POLARIZATION ON TWITTER?

by
SERHAT DEMİRKIRAN

Submitted to the Graduate School of Engineering and Natural Sciences
in partial fulfilment of
the requirements for the degree of Master of Science

Sabancı University
March 2025

ABSTRACT

HOW DID BABALATV CHANGE ONLINE POLARIZATION ON TWITTER?

SERHAT DEMİRKIRAN

DATA SCIENCE M.Sc. THESIS, MARCH 2025

Thesis Supervisor: Asst. Prof. ONUR VAROL

Keywords: BabalaTV, political polarization, social media, 2023 Turkish presidential election, echo-chambers, computational social science

Social media has become a crucial platform in democratic processes, reshaping the public sphere by creating interactive spaces where individuals can engage with political actors and each other. However, its criticized for creating echo chambers, driven by factors such as homophily, selective exposure and social media feed algorithms, which limit exposure to politically diverse perspectives. In this study, we hypothesize that in countries like Turkey, where the media is heavily controlled and society is highly polarized, shows such as 'Mevzular Acik Mikrofon' with open Q&A format reduce the political polarization by offering public space free of censorship. To test this hypothesis, we collected data about the 'Mevzular Acik Mikrofon' videos posted on the YouTube channel BaBaLa TV, along with the other political discussion shows. Integrating with the #secim2023 dataset, we developed a ideology estimation model and applied it to examine changes in follower composition for guest politicians before and after their program appearances. Results shows that 'Mevzular Açık Mikrofon' opens a alternative channel to reach politically diverse audience, increasing exposure to different political messages. This in turn reduces the political polarization. Also, through the analyses of sentiment and linguistic variation of audience comments and transcript of show's videos, we further support our findings. These results contribute to broader discussions on the role of digital media in democratic processes and polarization dynamics

ÖZET

BABALATV, TWITTER'DA ÇEVRİMİÇİ KUTUPLAŞMAYI NASIL DEĞİŞTİRDİ?

SERHAT DEMİRKIRAN

VERİ BİLİMİ YÜKSEK LİSANS TEZİ, MART 2025

Tez Danışmanı: Dr. Öğr. Üyesi ONUR VAROL

Anahtar Kelimeler: BabalaTV, siyasi kutuplaşma, sosyal medya, 2023 Türkiye Cumhurbaşkanlığı seçimi, yankı odaları, hesaplamalı sosyal bilim

Sosyal medya, bireylerin siyasi aktörlerle ve birbirleriyle etkileşime girebilecekleri interaktif alanlar yaratarak kamusal alanı yeniden şekillendiren, demokratik süreçlerde çok önemli bir platform haline gelmiştir. Bununla birlikte, homofili, seçici maruz kalma ve sosyal medya akış algoritmaları gibi faktörlerin etkisiyle yankı odaları yaratarak siyasi açıdan farklı perspektiflere maruz kalmayı sınırlandırdığı için eleştirilmektedir. Bu çalışmada, medyanın yoğun bir şekilde kontrol edildiği ve toplumun yüksek oranda kutuplaştığı Türkiye gibi ülkelerde, açık soru&cevap formatlı 'Mevzular Acik Mikrofon' gibi programların sansürden arınmış bir kamusal alan sunarak siyasi kutuplaşmayı azalttığını varsayıyoruz. Bu hipotezi test etmek için, diğer siyasi tartışma programlarıyla birlikte BaBaLa TV YouTube kanalında yayınlanan 'Mevzular Acik Mikrofon' videoları hakkında veri topladık. Bu verileri #secim2023 veri setiyle entegre ederek bir ideoloji tahmin modeli geliştirdik ve bu modeli konuk politikacıların programa katılmalarından önce ve sonra takipçi kompozisyonundaki değişiklikleri incelemek için uyguladık. Sonuçlar, 'Mevzular Açık Mikrofon'un siyasi çeşitliliğe sahip izleyicilere ulaşmak için alternatif bir kanal açtığını ve farklı siyasi mesajlara maruz kalmayı artırdığını göstermektedir. Bu da siyasi kutuplaşmayı azaltmaktadır. Ayrıca, izleyici yorumlarının ve gösteri videolarının transkriptinin duygu ve dilsel çeşitliliğinin analizi yoluyla bulgularımızı daha da destekliyoruz. Bu sonuçlar, dijital medyanın demokratik süreçlerdeki ve kutuplaşma dinamiklerine rolüne ilişkin daha geniş tartışmalara katkıda bulunmaktadır.

ACKNOWLEDGEMENTS

First, I'd like to thank my supervisor, Dr. Onur Varol. A friend once described graduate studies as finding oneself in the middle of a dense forest, searching for a path, equipped only with a single guiding light. Throughout my master's journey, Onur hocam has been that guiding light—supporting and guiding me at every turn. Even though I might not have always been the best student, he has been the best supervisor I could ever have hoped for. I have learned so much from working with him.

I also owe thanks to my family. My brother, Ferhat, always believed in me and was there for me. His endless support gave me motivation and strength during difficult times. I feel very lucky to have such an incredible brother by my side.

Lastly, I want to express my appreciation to the VRL Lab members. In particular, Ali and Yasser have been my true companions — my 'yol arkadaşları' throughout this academic journey. Their constant support made the challenges easier and the good moments even better. I truly couldn't have made it without them. I wish them all the best in whatever comes next.

To my family...

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1. INTRODUCTION

Several studies depict Turkey as one of the most polarized countries in the world. Erdogan (2016); Erdoğan & Uyan-Semerci (2018); Lauka, McCoy & Firat (2018) One of the factors that drives this polarization can be traced back to the 2007 general elections in which the Justice and Development Party AKP started to adopt divisive populist rhetoric to gain support and win elections Aydın Düzgit (2019). These polarizing tactics in turn contributed to democratic backsliding greatly Somer (2019). In April 2017, a referendum was held and changed Turkey's political system from parliamentary to presidential system, leading to limited institutional checks and balances Esen & Gumuscu (2018). As a result of these gradual structural transformations by the regime, Freedom House changed the status of Turkey from partially free to free in 2018 House (2017)

The process of autocratization in Türkiye is accompanied by increasing control over media Yesil (2014). As governmental power has consolidated, independent news outlets and critical voices have come under mounting pressure, leading to a systematic erosion of press freedom. Journalists face legal challenges, economic sanctions, and pervasive surveillance, all of which contribute to an environment of self-censorship. The most prominent example of increasing media control was the period following the 2016 failed coup attempt. Recep Tayyip Erdoğan ordered a state of emergency for three months, subsequently extending it multiple times. This state of emergency granted the president extraordinary powers to issue decrees without parliamentary approval and bypass the Constitutional Court. Utilizing these emergency powers, the Turkish government shut down over 140 media outlets by the end of 2016 Griffen (2019). Later, the Turkish media landscape experienced another significant transformation. In March 2018, Turkey's largest media group Doğan Media Group was sold to Demirören Group with the support of substantial financing from Turkey's state-owned Ziraat Bank. The deal included major media outlets such as Hürriyet, Posta and Fanatik, as well as influential television channels like CNN Turk and Kanal D. Before this sale, Dogan Media Group had maintained a relatively balanced editorial stance and frequently faced criticism from government. When it is sold to Demirören Group, they started to adapt a more pro-government editorial stance in their reporting. This shift significantly reshaped Turkey's media environment, raising concerns among media watchdog organizations and observers about increasing media concentration, diminished journalistic independence, and growing governmental control over public discourse, ultimately undermining the foundations of democratic accountability Mill Mill (1998).

In a politically constrained environment, social media platforms became an alternative and significant source of information. One such example is the YouTube show 'Mevzular Açık Mikrofon', aired on the BabalaTV channel. This political discussion program featured important political figures from various backgrounds, including presidential candidates. What sets this show apart from other political talk shows is its interactive format, allowing the audience to engage directly by asking questions freely. The show quickly gained enormous popularity, with each video on the channel receiving millions of views. Its success peaked following the appearance of Barış Atay, a parliament member from the Workers' Party of Turkey. Following his appearance, his party experienced a 30% increase in membership, gaining 10,000 new members Pierre (2023)

Through this study, we provide several key contributions. First, it extends prior research on media polarization by exploring how alternative platforms—specifically BabalaTV, 'Mevzular Açık Mikrofon'—shape the polarization debate in a context where free media is restricted. We assembled a comprehensive dataset of all political discussion programs aired on YouTube, including those from 'Mevzular Açık Mikrofon', and integrated it with #Secim2023 dataset Najafi, Mugurtay, Zouzou, Demirci, Demirkiran, Karadeniz & Varol (2024). Our analysis reveals that appearances on 'Mevzular Açık Mikrofon' significantly enhanced the public outreach of guest politicians across online spaces; its challenging and critical format attracted considerably more attention than traditional program formats. Second, we examine the composition of politicians' followers before and after their appearances on these shows by applying follow-time and ideological point estimations. We demonstrate that BabalaTV has opened a new channel for reaching a more diverse media audience, increasing cross-cutting exposure. By facilitating political debates free from censorship, it enables the expression of a wide range of opinions and viewpoints. Lastly, we analyze the linguistic variation in the political discourse featured on 'Mevzular Açık Mikrofon' to further enrich our understanding of its role in the polarization debate.

Hypotheses

Recent research indicates that the utilization of social media enhances political participation Strömbäck, Falasca & Kruikemeier (2018). We propose that in countries where mainstream media encounters obstacles, alternative online television programs may exert a positive influence on the reduction of political polarization. In highly politicized environments, individuals frequently experience difficulties in communication, and the information disseminated through government-affiliated media is often subject to extensive filtration. Under these conditions, people are attracted to such programs as they provide opportunities to establish direct contact and engage in discussions with guests. Building on the previous research, we hypothesize that **alternative digital political media impacts the political behavior of social media users by augmenting overall engagement, diminishing like-minded clustering, and lessening polarization. This is particularly significant in contexts where the dominant media outlets are stringently controlled by governing authorities. We dissect our main hypothesis into sub-hypotheses for the sake of greater parsimony and precision.**

Numerous studies have shown that people respond to political debates on social media. YouTube'S unfiltered content is a contributing factor to the popularity of the platform's political content. Consequently, YouTube more likely to have a positive effect on people's attention to political debates English, Sweetser & Ancu (2011). To assess this hypothesis, we examine pre-and-post follower trends of specific politicians who appear as guests on Babala TV. We expect that politicians who showed up in Babala TV gains more followers after the event. This change in the follower trend contribute a politican's public outreach.

Hypothesis A: Political online broadcasting changes trends in politican's online public outreach.

Different from a politican's follower trends, polarization emerges as a significant issue. Polarization occurs when opposing viewpoints develop on an issue and become stronger as time passesGrover, Kar, Dwivedi & Janssen (2019).This matter has emerged as a vital discussion in shaping political discourse and consequences Douai (2019); Ledwich & Zaitsev (2019); Munger & Phillips (2022). The free nature of YouTube and its collaborations with traditional mainstream broadcasting services can contribute to the development of democratic ideals among its viewersMcKinney & Rill (2009). However, it can also provide diverse political actors to mobilize public sentiment Ekman (2014); Ledwich & Zaitsev (2019); Munger & Phillips (2022). Such debates put a question mark if social media platforms such as YouTube increases or decreases political polarization.

Follower increase might shows the Babala Effect, but it does not signal any information about the composition of followers. In recent years, social media has been well debated for its role in encouraging the emergence and resilience of echo-chambers, and political homophily has been identified as one of the negative consequences of social media use. It is possible that Babala Effect may contribute to crumbling echo chambers if it changes the composition of the follower network. This implies that we need to pay more attention to the de-polarization effect of the TV Show, based on the change in follower composition before and after the event. This hypothesis also touches depolarization debate, since we position each political party's follower clusters towards the political guest. Reasons behind their de-polarization effect reflect multiple dimensions of people's interest in these shows. First, shows like Babala TV present diverse perspectives. Alternative online TV shows often feature guests representing a variety of political, social, and economic perspectives. By promoting diversity, viewers will be encouraged to consider alternative viewpoints and gain a deeper understanding of the complexity of issues, thus reducing polarization. Second, online TV shows are not subject to the same level of censorship and control as traditional media, which allows them to present unfiltered information and discussions. In this way, viewers are able to access a wider range of content and form opinions based on a more comprehensive understanding of the issues involved. There is often an opportunity for viewers to participate in online TV shows through interactive features such as live chats, social media engagement, and the ability to submit questions. It promotes constructive dialogue between audience members and guest speakers and breaks down barriers between opposing viewpoints.

Hypothesis B: Political online broadcasting weakens political homophily, as it also decrease polarization among Twitter users.

2. Literature Review

2.1 Televised Debates

Television programs have long been an important medium for engaging the public Maier & Faas (2011), with televised political debates playing a crucial role during key political events such as elections. These debates often influence public reactions and participation Kalsnes, Krumsvik & Storsul (2014); Maier & Faas (2011). In recent years, the rise of social media has introduced a new dynamic to this phenomenon. People increasingly engage with online televised content while simultaneously participating in discussions, sharing their opinions, and reacting to political figures during or after these debates.

The impact of television shows on political behavior has been extensively debated, with no clear consensus about their influence. Some studies suggest that television programs encourage political participation Boukes & Trilling (2017); Patterson & McClure (1976), while others highlight their potential to discourage engagement Gentzkow (2006); Hayes (2009). For instance, Patterson et al. (1976) found that political advertisements provide less-informed voters with more accessible political information compared to traditional news coverage. Similarly, Maier and Fass, based on their studies of German elections, concluded that TV programs had a greater participatory effect on people with lower political interest Maier & Faas (2011). Sorensen (2019) also highlighted how modern TV broadcasting boosts political engagement Sørensen (2019). Furthermore, Maier and Faas (2011) observed that candidates who performed well during televised debates attracted more votes Maier & Faas (2011). However, other scholars argue that exposure to political television can sometimes amplify political polarization under certain conditions Arceneaux & Johnson (2010); Arceneaux, Johnson & Murphy (2012); Gondwe (2017), while some studies suggest the influence of televised content on behavior may be overstated Hayes (2009). Gentzkow (2006), for example, noted that television access in the United States reduced political participation, attributing this to the limited political content on TV Gentzkow (2006).

Although debates on the influence of television on political participation and polarization persist, these discussions take on new relevance with the rise of online media. In a global environment increasingly marked by authoritarian tendencies, social media has become a vital source for accessing alternative, uncensored information Levitsky & Way (2002)

We build upon the existing research on TV shows, online broadcasting, and political polarization to examine these subjects in the context of Turkey's general elections in 2023. These elections occurred during a period of ongoing democratic regression in Turkey, characterized by discussions around regime transformation, polarization, and press-party parallelism Bulut & Yörük (2017); Esen & Gumuscu (2016); Irak (2016); Metin & Morales (2022); Ogan & Varol (2017); Saka (2016); Toros (2015); Toros & Toros (2022); Varol, Ferrara, Ogan, Menczer & Flammini (2014); Yaman (2014); Yesil (2021). A filtered media landscape often goes hand-in-hand with increased polarization. Çarkoglu (2012) investigated and forecasted ideological and economic drivers of election results for 2002, 2007, and 2011, discovering that the prominence of ideology grew during this period Çarkoğlu (2012). In such an environment, alternative information sources become a crucial component of the democratic process Dahl (2005). The filtered main-stream media atmosphere in Turkey coincides with the nation's political polarization. Beyond regime fluctuations, political and ideological polarization emerges as one of the most pressing concerns ahead of the forthcoming elections. Consequently, social media and independent TV shows have become noteworthy subjects for discussion on social media platforms, particularly in relation to polarization.

YouTube, in particular, has become a key arena for political debates and advertising Vesnic-Alujevic & Van Bauwel (2014). As an innovative space for journalistic practices, it reflects the evolving dynamics of mass media and political communication Djerf-Pierre, Lindgren & Budinski (2019). YouTube is frequently used for political debates Hanson, Haridakis & Sharma (2011); Intyaswati, Intityaswi, Maryani, Venus & Sugiana (2019), but its role in increasing or reducing polarization remains contested García-Marín (2021); Hosseinmardi, Ghasemian, Clauset, Mobius, Rothschild & Watts (2021); Ledwich & Zaitsev (2019). This study examines the "Babala Effect," using Twitter as a lens to analyze the impact of YouTube content on political behavior and polarization. Twitter has become a battleground for political discourse, with opposition and ruling parties extensively using the platform

Ahmed & Skoric (2014); Baxter & Marcella (2012); Jungherr (2016).

2.2 Political Polarization and Social Media

2.2.1 Definition

There is no consensus on the conceptualization of polarization, measurement of polarization, and types of polarization. We can say that the field of political polarization itself is also polarized. In the political science literature, it is generally regarded that there are two types of polarization: ideological polarization and affective polarization. Ideological polarization is simply the measure of divergence of political attitudes across a spectrum. To measure the divergence, people are surveyed about their positions on various political issues, revealing their ideological placement along a liberal-conservative spectrum. Figure 2.1 shows two possible distributions of ideological orientations regarding polarization. Distribution at the bottom represents a nonpolarized society. The majority of individuals are positioned close to the center of the spectrum, showing most people holds moderate views across wide range of political issues. Whereas, we have a bimodal distribution at the top, showing a polarized society. Individuals consistently holds either liberal or conservative attitudes across the political issues.

2.2.2 Ideological Polarization

Based on this definition of ideological polarization, there has been controversies about whether US society is divided or not. We mention the US society since discussions about political polarization is originated from there and they have extensive empirical data to examine this phenomenon.

Contrary to widely accepted view, Fiorina and his colleagues rejected the idea of divided American society Fiorina, Abrams & Pope (2004). To support their claim,

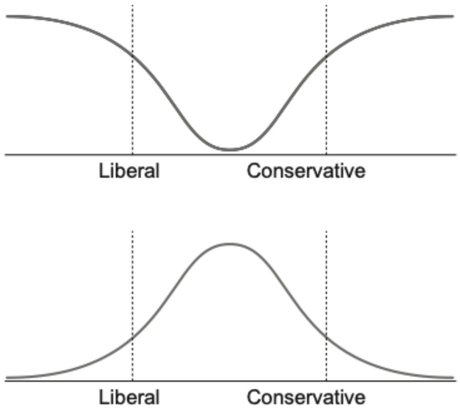

Figure 2.1 Distributions exhibiting polarization and no polarization. Source: Fiorina & Abrams (2008)

they examined the NES (National Election Studies), GSS (General Social Survey) and Gallup survey data Fiorina & Abrams (2008) NES provided participants 7 choice on a ideological scale. These include extremely liberal, liberal, slightly liberal, moderate, slightly conservative, conservative and extremely conservative. GSS also adapted a similar set of options for respondents. Whereas Gallup offered 5 distinct categories for their polls since 1970 (Very liberal, liberal, moderate, conservative, very conservative). When they examined the survey results over time, they concluded that there is no increased mass political polarization compared to previous generations. Figure 2.2 shows the shares of people choosed moderate or "don't know" option. Results show that for all surveys conducted over more than 30 years, share of moderates did not experience a major change. Majority of people still holds moderate views on political issues and a very small number of people consider themselves as extremely liberal or extremely conservative. Authors continue reporting that if they were an increased mass political polarization among US society, then the distribution of ideological orientations would widen over time.

These series of surveys provided data up to 2006. Subsequent surveys to the present day also presented similar trends. Proportion of liberals and conservative individuals among US society remained unchanged throughout the decades. For comparison, we also wanted to present results of surveys conducted by another credible research organization called Pew Research Center. Individuals identifying themselves as Republicans and Democrats asked about their views across political issues, then a distribution of ideology scores along party lines obtained. Figure 2.3 illustrates the distribution of Democrats and Republicans across a ten-point scale. Prior to 2004, the distribution of two parties largely overlapped, indicating minimal polarization. Distributions in previous years suggested it was very likely that people might have conservative attitudes on some topics but have liberal attitudes on other topics.

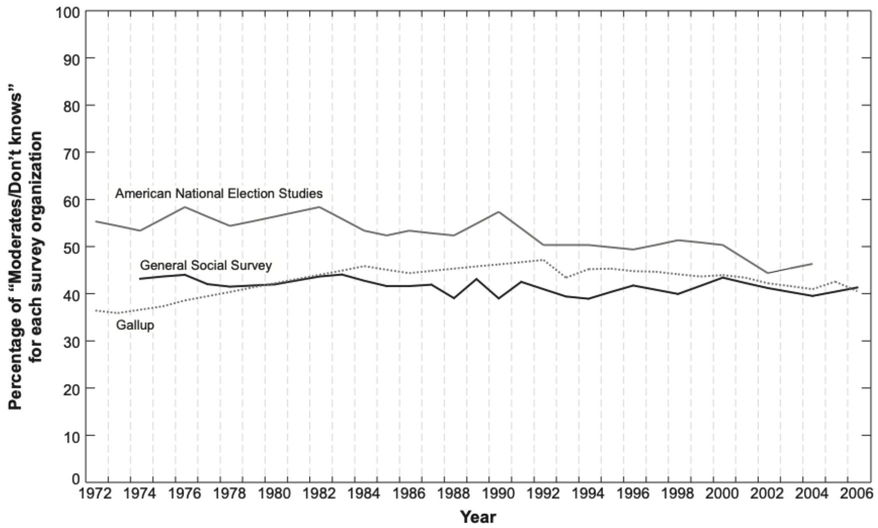

Figure 2.2 Relative fractions of moderates or undecided respondents reported across various surveys. Source: Fiorina & Abrams (2008)

However, since 2004, a significant divide has emerged between them. As we getting closer to present time, distance between median score of democrats and median scores of republicans significantly increased. This suggests that individuals consistently hold either liberal or conservative beliefs across the broad range of issues such as economic policy, immigration, healthcare, education, environmental regulation, and social values.

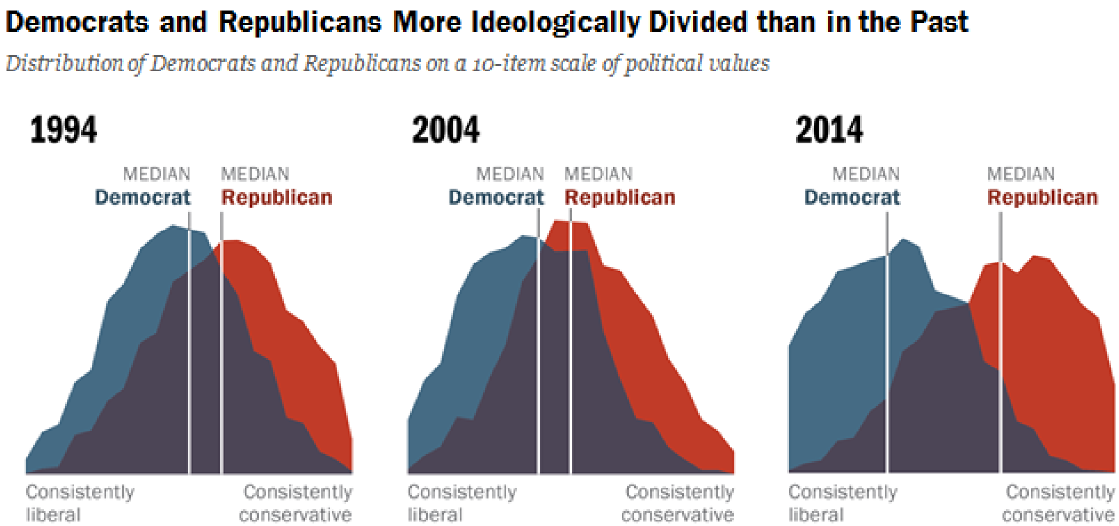

Figure 2.3 Political Polarization in the American Public, Pew Research Center

When the scholars examined the surveys data (NES, GSS, Gallup), they've concluded that there was no evidence to say that American society is deeply divided. Most of Americans holds moderate views while very small number of individuals have extreme views. Then, why is it the case that we see a substantial divide emerging between the distributions of Republicans and Democrats? Reason could be attributed to the greater alignment of one's partisanship and their ideology, namely partisan sorting. Studies showed that over time the fraction of sorted partisans has consistently increased Levendusky (2009) . As mentioned in above paragraph, in the past, more people were holding mixed views on political issues. This situation changed and people now consistently have either liberal or conservative views across issues.

2.2.3 Affective Polarization

Having talked about the measurement of ideological polarization and the level of it among society over time, there is also another type of polarization regarded in the political science literature. It is called affective polarization. It focuses on emotions and identity aspects rather than divides around political issues. As people adopt a political party as part of their identity, either be Democrats or Republicans, world is divided into two for them: a group of people who identify themselves with same party (in-group) and other group of people who identify themselves with other party (out-group). This is rooted in our tendency to categorize people around us based on their similarity/differences as a way to manage uncertainty. As a result of such a categorization, we naturally start developing negative feelings towards people from other party and positive feelings towards people from our party. This difference between in-group and out-group feelings reveals the level of affective polarization Iyengar et al. (2019).

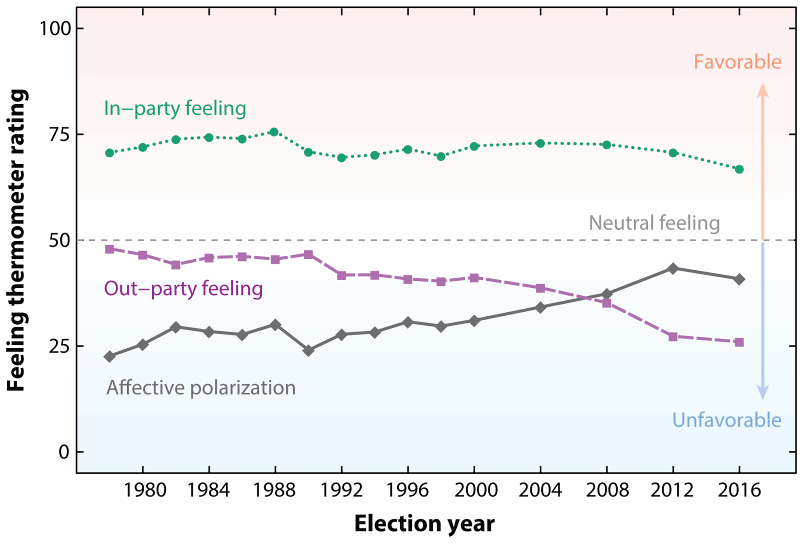

Figure 2.4 Feeling Thermometer. Source: Iyengar et al. (2019)

To study this phenomenon, scholars relied on the feeling thermometer data released by American National Election Studies (ANES) Iyengar, Sood & Lelkes (2012). ANES asks participants to rate party they identify with and other party in terms of feelings. Scores collected in a 0-100 numerical scale, lower scores show people feel cold and unfavorable towards party and higher scores shows they feel warm and favorable towards party. Figure 2.4 shows the ANES survey results. What we can observe is that starting with early 2000's, hatred towards out-party increased gradually, causing worsening affective polarization

2.2.4 Causes of Polarization

Several factors have been attributed to the rise of polarization worldwide. These include partisan sorting, rise of partisan news outlets, internet use, and others. Regarding demographic changes, it is considered as one of the biggest factors driving political polarization in United States. Ratio of non-white people within American population increased substantially in recent decades Erdoğan & Uyan-Semerci (2018). It is projected that in 2045 white people will no longer be majority. This rapid shift in US demographics reflected in the voting behaviours as well. The impact of internet access on political polarization is widely debated. Cass Sunstein, in his influential work 'Republic.com' Sunstein (2001), discussed how new communication technologies affect democracy. He argued that for deliberative democracies, people should not only encounter information that is aligned with their existing beliefs but also be exposed to diverse perspectives. However, in the age of algorithms, internet has the potential to foster the creation of echo chambers that reinforce their preexisting beliefs, leading to increased extremism. This argument is further supported by Pariser in the book 'The Filter Bubble: What the Internet is Hiding from You' Pariser (2011). Pariser argued that personalization in search engines and social media platforms leads to the emergence of bubbles, limiting our exposure to different views. As we increasingly spend time on these platforms, personalization algorithms learn our preferences, and they show us what we want to see.

Despite the seemingly widespread agreement, empirical evidence presented in Bakshy, Messing & Adamic (2015) suggested that personalization algorithms on Facebook slightly affect the exposure to cross-cutting content. Eytan Bakshy and his colleagues did a large-scale study on Facebook that includes over 10 million users who self identified their ideological orientation in the U.S. To examine cross-cutting exposure rates, authors identified 4 distinct stages. In the first stage, set of Facebook users randomly exposed to hard content (political content). In the next stage, similar to our offline interactions, users will be able to see hard content that shared by their friends. Third stage introduces feed algorithms, which ranks the contents and changes what people see on their timeline. And lastly, users do some choices by clicking the content they exposed to. They showed that when there is no network or ranking effect, over 40% percent of hard content liberals and conservatives exposed turned out to be cross cutting. When potential from network introduced, this figures dropped significantly, 24% for liberals and 35% for conservatives. In the next stage, it is indicated that the newsfeed algorithm decreased exposure to cross-cutting content by 8% for individuals identifying as liberals and 5% for those identifying as conservatives. Finally, what they report is individual choices at the end has greater impact on reducing encounters with opposing viewpoints than News Feed algorithm

Another component that is believed to foster political polarization and echo chambers is homophily, the natural tendency to connect with similar people. Several studies have demonstrated the impact of homophily on online communication networks.For instance, Adamic & Glance (2005) examined linking patterns within and between political blogs preceding the 2004 U.S. election. They found a prominent divide in network structure, with most linking happening within the ideological clusters. Conservative blogs are more likely to link to conservative blogs and liberal blogs more likely to link to liberal blogs. Cross-cutting linking is found to be limited. Another influential work by M.D. Conover and his colleagues examined the communication structure on Twitter preceding the 2010 U.S. election Conover, Ratkiewicz, Francisco, Gonçalves, Menczer & Flammini (2011). Their finding was consistent with previous studies. Identifying 250,000 political tweets over six weeks preceding the 2010 U.S. elections, they constructed political retweets networks and political user-to-user mention networks. Findings showed that, for retweet network, political communication is highly segregated along ideological lines. There are two clear homogeneous cluster with limited connection between them. The majority of information exchanges happened within the clusters. Liberal individuals tend to retweet tweets from other liberal users and conservative individuals tend to retweet other conservative users. However, for the political user-to-user mention network, there is a one big heterogeneous cluster. Mentions and replies are more likely to lead to exposure to cross-cutting interactions. A similar study done by Pablo Barbera and his colleagues. Examining 150 million tweets regarding political and nonpolitical topics, authors investigated if the communication in social media looks like an echo chamber or not Barberá, Jost, Nagler, Tucker & Bonneau (2015). To test it, they studied how retweeting activity varied across issues such as '2012 election', ‘Government Shutdown’, ‘Boston Marathon’, ‘Syria’ and so on. Consistent with the Conover’s work, they found that majority of retweeting happened among like-minded individuals regarding political issues. Liberal people mostly retweeted other liberal people and conservative people mostly retweeted other conservative users. However, regarding non-political issues such as Boston Marathon, they didn’t observe such polarization

These body of work in literature provided empirical evidences to show that social media creates echo chambers in which you isolated and don’t hear other sides. However, there is an another body of work in literature that challenges this view. They suggest that contrary to popular belief, social media does not lead to the echo chambers and increase the mass political polarization. Pablo Barbera in a later work of his claimed that social media increases cross-cutting exposure and reduce the political divide Barberá (2014). To quantify the exposure to diversity, he considered the proportion of user’s twitter network who do not have similar ideological orientation. For a conservative user, that would be the fraction of liberal people in his network. As this quantity goes up, users will more likely to expose to different political views. Measure close to 0 would represent no diversity and measure close to 0.5 would represent no homophily. Defining this framework, author found that in Germany and Spain, in average, 44% and 45% percentage of user’s network have different ideological orientation respectively, reflecting high rate of encounter to opposing views. In consistent with the other works in literature, United States has slightly lower rate of exposure to diversity with the 33%. Another work by Boxel and his colleagues also rejects the idea that internet is the main driver of political polarization. Their findings reveal that level of polarization is highest across the group of population which is less likely to use social media Boxell, Gentzkow & Shapiro (2017).

2.3 Turkish Case

To better examine the polarization debate in Turkey, it is essential to trace its origins to the foundation of the secular republic in 1923. Mustafa Kemal Atatürk, the founder of the Turkish Republic, implemented a series of reforms aimed at modernizing and westernizing the nation. These reforms included the abolition of the caliphate, the closure of religious schools, promoting secular education, and significantly diminishing Islam’s role in public life. Such top-down measures generated deep societal divisions. Şerif Mardin interpreted these developments as a conflict between a political elite advocating Western values and a society resistant to such transformations Mardin (1973). This foundational divide has continued to shape Turkish politics, societal dynamics, and national identity since the establishment of the Republic.

Throughout much of the 20th century, the secularist elite—operating through key state institutions such as the military and the judiciary—maintained control over Turkish politics, often marginalizing conservative and Islamist movements. However, the political landscape shifted with the rise of the Justice and Development Party (AKP) in 2002, under the leadership of Recep Tayyip Erdoğan. Initially, the AKP pursued a moderate reformist agenda, emphasizing European Union (EU) accession and economic development. Over time, however, the party increasingly adopted a populist and divisive approach, particularly in response to resistance from the secularist establishment. Events such as the 2007 presidential election crisis, mass protests, and judicial interventions further intensified political polarization. Both secularist and Islamist factions came to perceive each other as existential threats to their respective visions of Turkey Aydın Düzgit (2019).

Contemporary Turkey shows heightened polarization, which has been extensively documented in academic studies. The survey "Dimensions of Polarization in Turkey" Erdogan (2016) highlights significant social divisions, including high levels of social distance, moral superiority, and political intolerance in Turkish society. To measure these levels, respondents were first asked to identify the political party they felt closest to and the one they felt most distant from. 83% of respondents disapprove of their daughter marrying someone who supports the party they feel most distant from. Additionally, 74% do not want their children playing with the children of someone who votes for that party, and 78% refuse to do business with a supporter of that party. This intense polarization is attributed to multiple factors, including frequent elections and referendums, divisive rhetoric from political elites, and the prevalence of "echo chambers"—environments where individuals are surrounded by like-minded people and rarely exposed to opposing views. Moreover, rather than working to reduce polarization, politicians often exploit it to mobilize their supporters.

3. Methodology

3.1 Dataset

To examine the BabalaTV effect , we used #secim2023 dataset(Najafi et al., 2024). Accounts of various Turkish politicians and media outlets identified on the social media platform Twitter. Currently it covers 1435 accounts. Having this accounts, dataset regularly collected their networks (friends, followers) and profile statistics. Profile statistics include metadata values such as user's id, account creation date, screen name, display name and so on. For our study, we used these fields: followers_count for the number of followers the user currently has, friends_count for the number of account the user is following and lastly statuses_count for the number of tweets (retweets included) the user posted. Followers_count allowed us to keep track of politician's daily follower number changes. Also, we used friends_count and statuses_count to assess account's activity level for our ideology estimation model. Furthermore, the dataset includes collections of tweets related to predetermined keywords and a curated list of political accounts to capture political discussions. This enabled us to monitor the level of discourse surrounding guest politicians after their appearances on broadcasts.

In addition to twitter dataset #secim2023 , we compiled a list of political discussion broadcasts on Youtube. This list includes programs 'Liderler Özel' on the Sözcü channel, 'Teke Tek' on the Habertürk channel, 'Uğur Dündar ile Haftanın Panoraması' on the TV100 channel, 'Liderler FOX'ta' on the NOW Haber channel, and 'Mevzular Acik Mikrofon' on the BabalaTV channel. Moreover, we identified the joint broadcasts featuring Recep Tayyip Erdoğan, titled 'Cumhurbaşkanı Özel Yayın', which aired on channels such as TRT Haber, 24 TV, CNN Türk and ÜLKE TV with the name 'Cumhurbaşkanı Özel Yayın'. Except for Erdoğan's joint broadcasts, all mentioned channels shared a playlist on their Youtube channel that included these programs, which aired in the lead-up to the 2023 presidential election. For each program, we prepared tables providing details about the guest politicians, their party affiliations, the dates they appeared, and engagement metrics such as the number of views and comments on the videos

Among these programs, ‘Mevzular Açık Mikrofon’ stands out for its open Q&A format, where the audience could directly interact with guest politicians by asking questions. The program hosted prominent and often controversial political figures. Together with the free space provided, program has been a great success. Each broadcast received millions of views. Unlike other programs, a teaser was also released along with the full broadcast. Also, Oğuzhan Uğur, the host of the program, regularly announced the upcoming episodes on his Twitter account weeks in advance. To better capture the impact of this program, we included the teaser release dates and the dates of Uğur's tweets announcing each guest in the corresponding table 3.1. Further details about the other broadcasts are provided in Appendix A.

Table 3.1 BaBaLaTV Program and Social Media Metrics(Values marked with * are in millions; values marked with ** are in thousands).

Participant	Party Affil.	Annc.	Teaser	Broadcast	Views*	Comments**	X Follower Count*
Ümit Özdağ	Zafer	27/07/22	01/08/22	04/08/22	10,1	48,1	1,6
Faruk Gergerlioğlu	HDP	01/08/22	14/08/22	18/08/22	11,8	53,2	0.4
Muharrem İnce 1	Memleket	17/08/22	27/08/22	01/09/22	13,9	32,3	5,9
Cem Uzan	Genç Parti	03/09/22	18/09/22	22/09/22	9,9	20,5	0,7
Ahmet Davutoğlu	GP	03/09/22	27/09/22	06/10/22	7,9	17,9	5,9
Metin Külünk	AKP	17/11/22	30/11/22	05/12/22	7,8	25,6	0,4
Barış Atay	TİP	02/01/23	08/01/23	12/01/23	23,0	44,0	2,2
Abdüllatif Şener	CHP	13/01/23	18/01/23	26/01/23	6,9	13,5	0,7
Muharrem İnce 2	Memleket	01/04/23	13/04/23	17/04/23	13,1	70,7	5,9
Sinan Oğan	ATA İttifakı	14/04/23	22/04/23	24/04/23	16,6	50,3	1,4
Ali Babacan	DEVA	16/04/23	26/04/23	02/05/23	5,7	22,2	1,1
Kemal Kılıçdaroğlu	CHP	19/05/23	23/05/23	24/05/23	29,5	227,3	11,1

3.2 Follower composition

Previous studies to examine political polarization and exposure to diversity extensively utilized interaction networks on social media (Conover et al., 2011), (Barberá et al., 2015). In this study, our approach is based on to assess how guest politicians’ follower network characteristics change around the date they appear on the Mevzular Acik Mikrofon. My goal is to see if politicians are reaching out to a diverse audience.

As discussed in the dataset section, the #secim2023 dataset (Najafi et al., 2024) enabled us to track the daily changes in follower numbers for political accounts. This was the starting point to examine BabalaTV effect. To conduct a more detailed analysis, we required additional information, such as identifying the new followers who began following guest politicians after their appearance on the program.

Normally, Twitter does not share the information about exactly what time a user started following an another user. However, the list of a user's followers can be retrieved in reverse chronological order. By exploiting the creation dates of these accounts, it is possible to infer approximate following times(Zouzou & Varol, 2024), (Meeder, Karrer, Sayedi, Ravi, Borgs & Chayes, 2011). In addition to following times, we developed an ideology estimation model to analyze shifts in the follower composition of politicians, particularly around the dates they appeared on the program. More details is given in next section.

3.2.1 Ideology Estimation

Previous academic research used numerous approaches leveraging social media data for ideology score estimation. Some relied on qualitative content analysis (Conover et al., 2011), while other scholars followed a practice in which they look at the URLs user share (Cinelli, De Francisci Morales, Galeazzi, Quattrociocchi & Starnini, 2021; Hohmann, Devriendt & Coscia, 2023). Each media outlet is associated a score ranging between $[-1, +1]$ putting them in a spectrum. Then, opinion score of users becomes average score of URLs they share. In this study, we follow a approach introduced by Pablo Barbera (Barberá, 2015; Barberá et al., 2015), which utilizes social media following patterns to estimate ideological positions. This method is grounded on the assumption that social media users tend to follow political figures whose ideological positions align with their own preferences. Estimation process involves several key steps:

3.2.1.1 Data Preparation

Mapping Followers to Politicians and Data Filtering

First, we construct an adjacency matrix mapping each follower to the politicians they follow. In the matrix, entry $a_{ij} = 1$ if user i follows politician j, and 0 otherwise. To ensure the estimation is robust, we applied the following filters to the follower dataset. Users must follow at least three politicians to be included in the analysis, ensuring sufficient political engagement for reliable estimation. The account activity criteria require a minimum of 10 tweets posted, at least 25 followers, and at least 25 accounts followed. Additionally, account validity checks include a maximum bot score of 0.7 to exclude automated accounts, measured using BotometerLite.

3.2.1.2 Model Fitting and Estimation

After filtering out our dataset, our working corpus comprised 4.4M unique follower accounts and 1435 political actors. Then we analyzed this dataset through Correspondence Analysis (CA). CA is a dimensionality reduction technique similar to Principal Component Analysis, and it is well suited for categorical data rather than continuous data. It allows us to capture relationship between entities on a lower dimensional space. Figure 3.1 shows the scree plot for our correspondence analysis (CA) of the political accounts-follower network on Twitter. The first dimension alone accounts for nearly 1.5% of total inertia, and the second for nearly 1%, together capturing 2.5% Although these percentages seem small, they are typical when CA is applied to very large, sparse binary networks Metin & Morales (2022). Prior studies showed that first two dimensions were able to capture partisan structure in political spheres of various countries Barberá et al. (2015); Gaughan (2024).

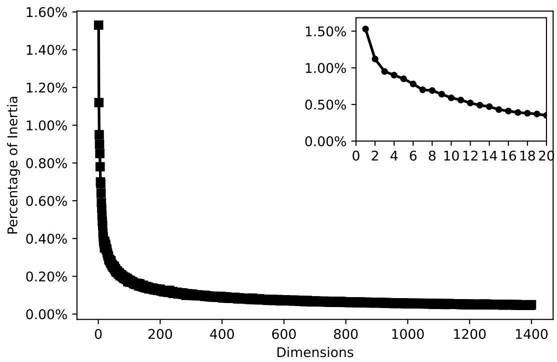

Figure 3.1 Scree plot

Figure 3.2 illustrates the positioning of politicians in a two-dimensional space, with colors representing their political party affiliations. The figure clearly shows that politicians from the same party tend to cluster together. The first component aligns with the current left/right ideological spectrum in Turkey. For our analysis, we focus on the first principal component (PC1) to investigate shifts in the follower composition of participants.

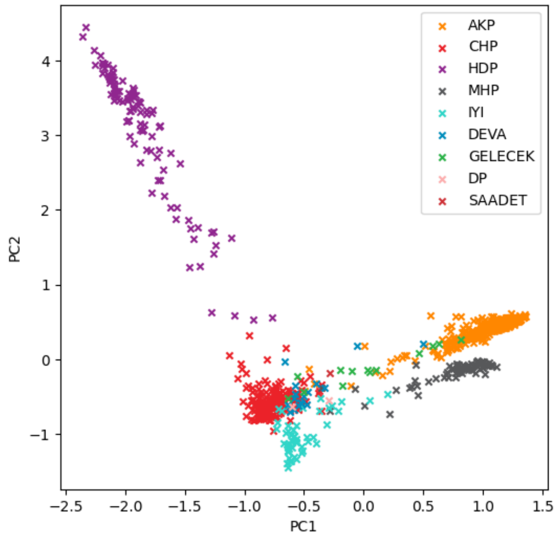

Figure 3.2 Ideological point estimation for politicians

Figure 3.3 illustrates the ideological distribution of ordinary users and politicians along a political spectrum. Ordinary users (solid blue line) display a distinct rightward skew; in contrast, politicians (dashed green line) exhibit a broader and more balanced ideological distribution, spanning across both left and right segments.

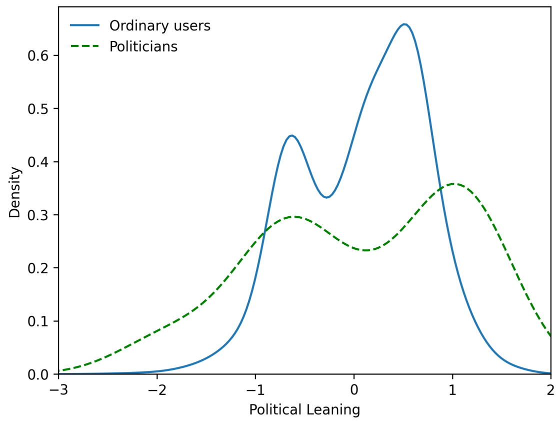

Figure 3.3 Ideology scores distribution

3.2.2 Bootstrapping Method

Having ideology estimation score enabled us to compare the shift in follower compositions of BabalaTV participants. Using these ideology scores, we then calculated density ratios for regular intervals within ideological spectrum. To set confidence intervals on densities and density ratios, we employed bootstrapping method. It allowed accurate estimation without relying on strict assumptions about the underlying distribution. In the bootstrapping method, samples are selected randomly with replacement from the original observed dataset. These randomly drawn samples are called bootstrapping samples. We repeated this sampling process 1000 times and calculated relevant parameters for each iteration. Subsequently, we constructed a distribution of these parameters obtained from bootstrap samples. The 95 % confidence interval was then determined by identifying the interval between the 2.5th and 97.5th percentiles of this distribution.

3.2.3 Bimodality Score

To compare follower compositions before and after participants appear on the show, our first approach was to calculate daily average ideology scores of new followers around the date participants appear on the show. In addition to that, to capture the distribution of followers' ideology scores, we used bimodality coefficient. Two group of followers with identical means can exhibit different shapes, one may be unimodal and the other might be multimodal. To detect this, BC combines skewness (g) and kurtosis (K*) to measure multimodality.

$$B_c = \frac{g^2 + 1}{K^* + \frac{3(n-1)^2}{(n-2)(n-3)}}$$

Values exceeding approximately 0.55 indicate that the distribution is more likely to be bimodal or multimodal rather than unimodal, whereas values below this threshold typically suggest a single-peaked (unimodal) distribution.

3.3 Youtube Analysis

YouTube has emerged as an alternative platform for political communication, providing a unique place for two-way interaction between the public and politicians. Unlike traditional media, YouTube allows viewers to actively engage through comments, sharing their opinions and reactions in real-time. To examine audience responses to the programs on BabalaTV and analyze how discourse changes across episodes, we conducted a comprehensive analysis of video transcripts and comments.

3.3.1 Data Collection

The video transcripts were obtained directly from YouTube using its automatic transcription feature. These transcripts, covering 12 selected videos listed in Table 3.1 were extracted and manually corrected to prevent errors arising from automated speech recognition. Youtube comments for videos of Mevzular Acik Mikrofon program on BabalaTV were collected using the YouTube Data API. The extracted comments include metadata such as the comment text, author display name, timestamp, and so on. The inclusion of author names is particularly valuable, as it enables the analysis of sentiment polarization among common commenters.

3.3.2 Sentiment Analysis

Sentiment analysis is one of the key NLP downstream tasks to evaluate the emotions expressed in a given content. In the context of polarization, it allows us to examine how one's feelings towards politicians from diverse backgrounds differ. For our purpose, we utilized a fine-tuned BERT model on the sentiment analysis task (Yildirim, 2024).

BERT(Bidirectional Encoder Representations from Transformers) is a pre-trained language model developed by Google (Devlin, 2018) and has set new standards for numerous natural language processing (NLP) tasks. It uses Masked Language Model (MLM) as the training objective in which %15 of tokens are randomly masked and replaced with the [MASK] token. Then, model tries to predict the masked token.

Building on this architecture, various language models have been developed in the Turkish natural-language-processing community, including TurkishBERTweet Najafi & Varol (2024) , BERTurk Schweter (2020), ConvBERTurk and so on. **Turk-**

ishBERTweet is trained on an exceptionally large corpus of 894 million Turkish tweets, features roughly 163 million parameters, and supports input sequences up to 128. **BERTurk** is pre-trained on a 35 GB mixed-domain Turkish corpus and contains about 185 million parameters. For our analysis, we used a fine-tuned version of BERTurk. The model outputs a label, either positive or negative, along with a sentiment score ranging from 0 to 1. Higher scores indicate greater confidence in the model's predictions.

3.3.3 Information extracting

To identify key themes and determine whether the topics discussed in the program resonated strongly with the audience, we conducted a word frequency analysis. To ensure the accuracy and reliability of the results, the analysis was preceded by several preprocessing steps to prepare the text for examination.

Turkish presents unique challenges for text analysis due to its complex morphological structure. Words in Turkish are formed by combining roots with sequences of suffixes, which can significantly alter their form. For accurate vocabulary statistics, it is essential to consider the base forms of words. For instance, words like kitapları (their books) are reduced to kitap (book), and evimizde (in our house) is reduced to ev (house). Without this lemmatization, inflected forms of the same word would disrupt the distribution, leading to misleading results.

To address this, we utilized a trained pipeline from the spaCy library (Altinok, 2023). The processing begins with tokenization, where text is segmented into discrete units such as words, punctuation marks, and other elements. Subsequently, each token's base form is identified using rule-based methods and lookup tables. Additionally, stop words −common function words like ve (and) or bir (a)—were removed during processing since they do not carry meaningful information for analysis.

The next step involves calculating the relative frequencies of lemmas in the corpus obtained after applying the preprocessing steps. For each word, we computed the log ratio $\log\left(\frac{P(\text{word}|\text{politician})}{P(\text{word})}\right)$ for both comments and video transcripts. This metric captures whether a specific word appears more or less frequently in a given program compared to other episodes of Mevzular Açık Mikrofon.

4. Results & Discussion

4.1 Online public outreach

As we have seen in Table 3.1, each program aired on Mevzular Acik Mikrofon series received significant engagement compared to other series of political discussion broadcasts presented in Appendix A. The program's format, which involves direct audience interaction and controversial political figures attending the program, made it very popular among the political discussion programs. One of the most popular and controversial show in the Mevzular Acik Mikrofon was the one that Barış Atay from Türkiye Worker Party attended. In the 2018 parliamentary term, he served as a representative of the HDP, a leftist party advocating for minority rights. Due to purported connections between the HDP and the banned Kurdistan Workers Party (PKK), it's been a sensitive issue among the public. When discussing issues related to these, tension amplified throughout the program.

We've seen that program on Youtube grabbed quite attention from the public. We further wanted to evaluate the effect of participating Mevzular Acik Mikrofon-BabalaTV on among the other platforms, namely Twitter, Wikipedia and Google Search.

Figure 4.1 shows how participating program affects Baris Atay's visibility. There is a clear trend of increased attention. After he appeared on the program, number of daily new followers and tweets posted regarding him increased significantly. Similar patterns were observed for Wikipedia page views and Google search activity. Results for other participants of Mevzular Acik Mikrofon are shared in Appendix A.

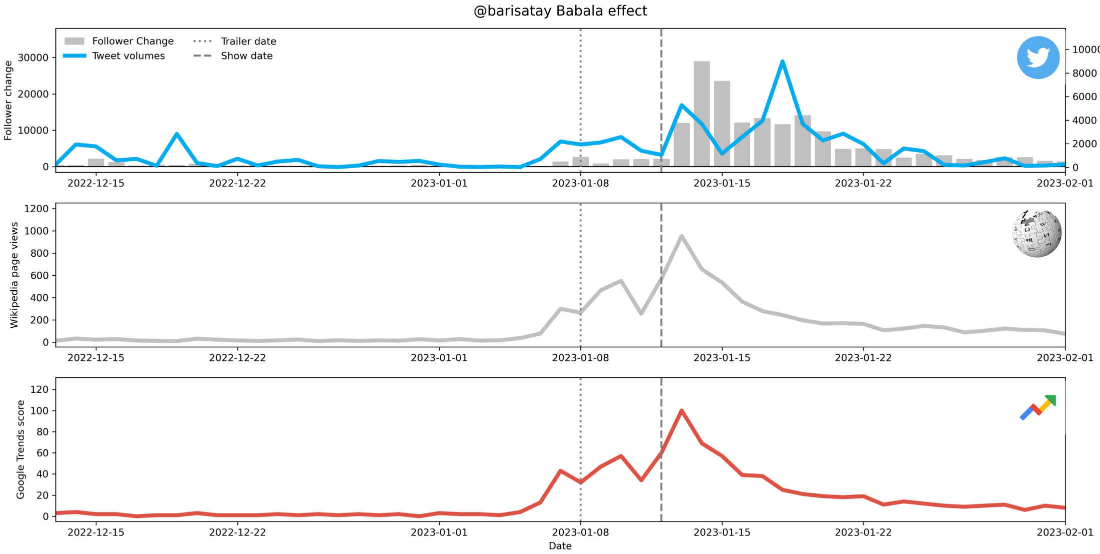

Figure 4.1 Effect of participating the BaBaLa TV show “Mevzular Açık Mikrofon.” Increased activity of search and information seeking behavior observed on Google Trend and Wikipedia. The guest also attract more followers and online discussion on Twitter.

For the initial participants of BabalaTV - Mevzular Açık Mikrofon, changes in tweet volumes are unavailable due to the dataset’s limited coverage of those periods. However, the impact of participating in the program remains evident through other indicators. In contrast, when examining the participation effects for other online debate shows (Habertürk - Teke Tek, TV100 - Uğur Dündar ile Haftanın Panoraması, Sözcü - Liderler Özel, NOW Haber - Liderler Fox’ta) A, no systematic impact was observed.

4.2 Political Polarization on Twitter

As previous analysis showed, ‘BabalaTV - Mevzular Acik Mikrofon’ provided strong public engagement in the presence of high government control over mainstream media outlets. Guest politicians attracted numerous followers after they appeared on Mevzular Acik Mikrofon. Now, we turn to follower composition. Change in follower composition suggests attracting a more ideologically diverse or moderate audience to their Twitter account. To examine follower composition change before and after they appear on Mevzular Acik Mikrofon - BabalaTV, we employed the ideology estimation tool described in the previous section.

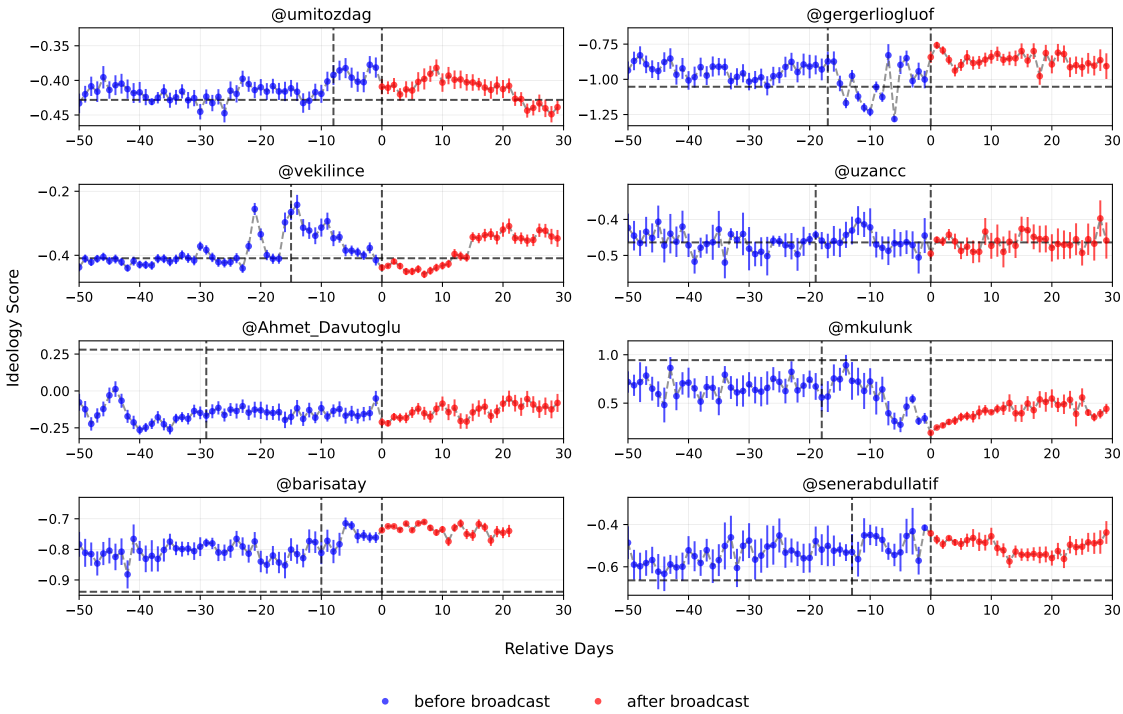

Figure 4.2 Follower composition change before and after guest politicians appear on the Mevzular Acik Mikrofon. The graph shows the average daily ideology scores of new followers around show date. Horizontal line represents participant's estimated ideology scores. Vertical line on left shows announcement date of program and vertical line on right shows the broadcast date.

We identified that change in follower composition varied across participants. Figure 4.2a shows the daily average ideology score of new followers for participants around the broadcast date on YouTube. The most prominent change was observed for the program that Metin Kulunk appeared in. Metin Kulunk is a former member of the Turkish Parliament from the ruling AKP (Justice and Development Party). He was the first and only participant from AKP. Before the announcement of his participation, ideology scores of new followers were relatively higher. Just after the announcement date, we see a noticeable downward trend in the scores. Just after the broadcast date, there is a sharp decrease to around 0.2. The post-broadcast scores are consistently lower than the pre-broadcast scores. These results indicate that the broadcast appears to have attracted followers with more moderate ideology scores. There is a clear shift in the follower base's ideological composition after the broadcast. Similar trends were observed for the participants such as Baris Atay and Umit Ozdag as well.

As it can be seen in table 3.1, Baris Atay's program was another special case among all the programs. His appearance on the program received the most engagement after Kemal Kılıcdaroglu. As mentioned before, he holds a controversial position because of his former party affiliation with HDP which has a close connection with PKK. Plenty of questions were directed to him by the nationalist majority audience in the program. However, the way he communicated his views along with his responses to the critics was very well received by the audience, as indicated by the shift in follower composition change.

Robustness checks with 2 sampling designs

For robustness checks we employed two random sampling strategy. Firstly, to isolate the composition-changing effect of the broadcast, we resampled the after cohort from the participant's pre-broadcast followers, matching the daily sample sizes. Assumption is in the absence of the broadcast, any new followers would be drawn at random from the pre-broadcast ideological distribution. Any divergence between the comparison group and the actual post-broadcast followers reflects the composition change. Second, we sampled from the pool of users who followed other guests but have not followed the participant yet. This group was exposed to the identical episodes and demonstrated recent follow activity. Figure 4.3 and Figure 4.4 displays the two strategies respectively. In each panel, the blue line traces the mean ideology of pre-broadcast followers, the red line shows actual new-follower ideology, and the grey line plots the randomized comparison. Shaded ribbons shows 95% bootstrap confidence intervals (1000 replications), and vertical dashed lines shows announcement and broadcast dates.

In Figure 4.3, when we look at the sampled post-broadcast scores compared to actual post-broadcast scores, for several guests the two curves diverge. Actual post-broadcast mean follower ideology scores of Barış Atay, Metin Külünk and Ömer Faruk Gergerlioğlu deviate noticeably from the random-sampled baseline, suggesting that the broadcast changed the follower composition of their audiences. For other politicians, actual post-broadcast and randomized curves remain aligned. Turning to Figure 4.4 we can see that program-wide flux goes around -0.5 on our scale and for most of the guest politicians it is noticeably different from their pre-broadcast base. For Cem Uzan and Abdullatif Şener, this flux is closely aligned with their audience. Ahmet Davutoglu, once served as Turkey's prime minister, does not seem to attract politically more distant audience. In first strategy, it shows little separation between the red and grey lines although program-wide influx sits below its actual pro-broadcast scores as can seen in second strategy

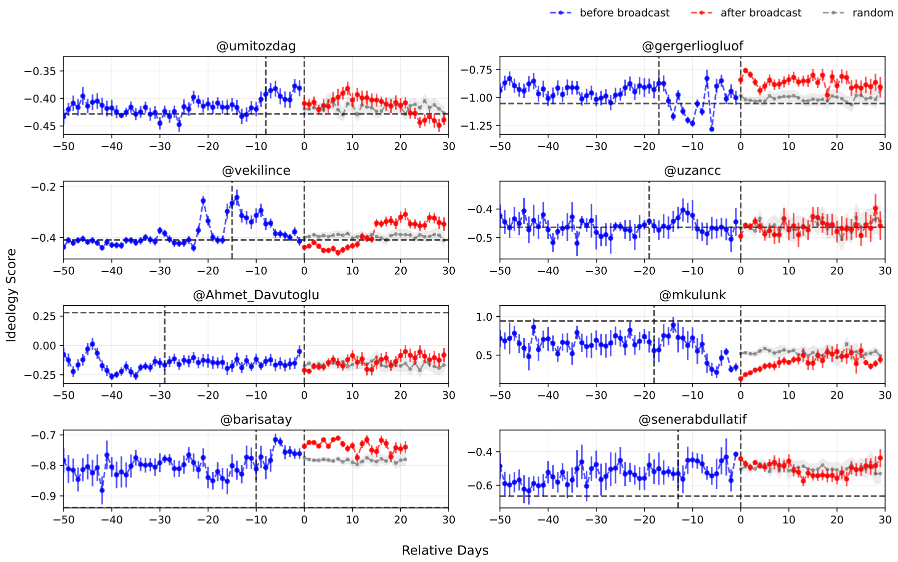

Figure 4.3 Follower composition change before and after guest politicians appear on the Mevzular Acik Mikrofon. Grey shows random sample drawn from the pool of pre-broadcast followers. Ribbons are 95% bootstrap CIs Horizontal line represents participant's estimated ideology scores. Vertical line on left shows announcement date of program and vertical line on right shows the broadcast date.

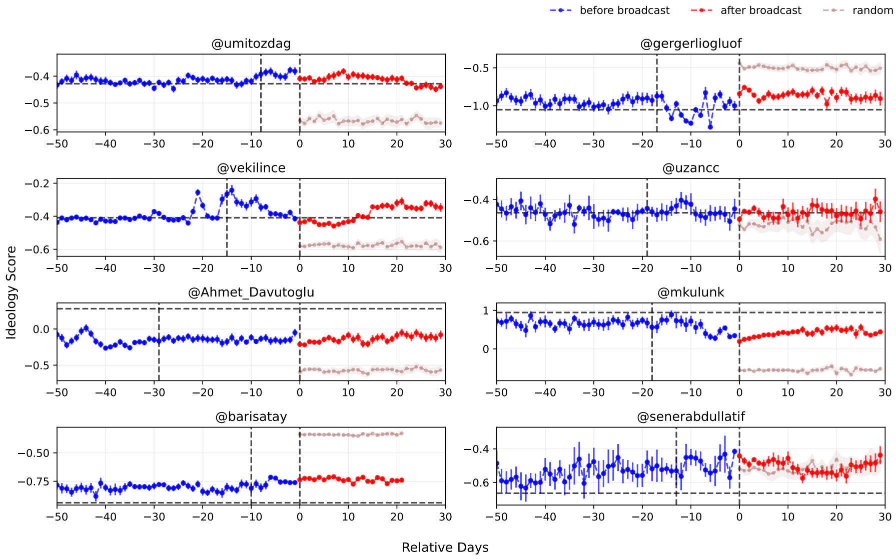

Figure 4.4 Follower composition change before and after guest politicians appear on the Mevzular Acik Mikrofon. Grey shows random sample drawn from the pool of users who followed other guests but haven't followed the participant yet. Ribbons are 95% bootstrap CIs Horizontal line represents participant's estimated ideology scores. Vertical line on left shows announcement date of program and vertical line on right shows the broadcast date.

To closely see how diverse new followers are, we compared ideological-score distributions of new followers who started followed participants in the 15 days before and after the broadcast appearance, together with bootstrapped 95% confidence bands. Figure 4.5 shows such analysis for Metin Külünk. We know from previous analysis that after Metin Külünk appeared on the 'Mevzular Acik Mikrofon' show, there was a clear shift in his follower base's ideological composition. To dive deeper, we contrasted the distributions across ideological segments. Lower subplot shows the log density ratio, so that values > 0 indicates ideological segments that became over-represented following the appearance, whereas values < 0 mark segments that became under-represented. The dashed vertical line is the Metin Külünk's estimated ideology.

The most notable change occurs in the extreme-left bin, where the log-ratio exceeds 2. However, due to the wide confidence interval, indicating high uncertainty, this result should be interpreted cautiously. The absolute numbers are small and could be driven by noise. Despite these limitations, it might suggest that politically distant viewers intentionally engaging with opposing viewpoints to stay informed, potentially weakening partisan echo chambers at the ideological extremes.

Figure 4.6 shows the distributions and corresponding log-density ratios of followers who started following Barış Atay before and after his appearance. At first glance, the overall distributions appear quite similar. However, on the extreme left, the log-ratio goes down to nearly -1.2, with Cis that do not cross zero. Highly left-leaning users were therefore less likely to start following after the appearance. Around the Atay's own ideology scores, log-ratio goes around 0 with narrow CI, showing little ideological mobilization. However, the ratio climbs gradually as we go right on the spectrum. There is a modest rise in centre-right followers in the two weeks following the show relatively. For the far right tail, the ratio turns negative again but CI widens sharply, showing high uncertainty.

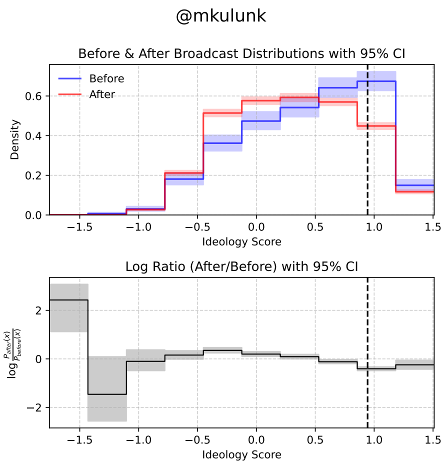

Figure 4.5 Top panel: Step-histograms of ideology scores for the new followers of Metin Külünk during the 15 days before (blue) and after (red) his broadcast appearance, with 95% bootstrap confidence bands shaded around each curve. The black dashed line marks the guest's own estimated ideology score. Bottom panel: Log density ratio across the ideology spectrum with 95% confidence intervals (gray). Positive values indicate ideological bins in which the share of new followers increased after the appearance, whereas negative values denote a relative decline.

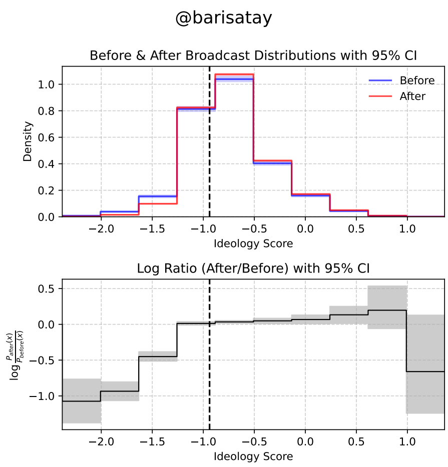

Figure 4.6 Barış Atay

Absolute Distance Distribution Comparison

As mentioned in the methodology part, to investigate the shifts in the follower composition of guest politicians, we focused on the first principal component (PC1). Throughout the previous analysis in this section, we utilized this component which aligns with the current left/right ideological spectrum Turkey. Compared to first principal component, it is a little bit harder to interpret the second principal component. Looking at the y-axis, on the one end we have the isolated placements of HDP members. On the other end, there are other parties which relatively get less votes from Kurdish citizens. This dimension might be associated to ethnicity divides in Türkiye. To analyze both of the principal components, we integrated the PC2 as well. In the previous density ratios analysis, we compared the distributions of ideology scores of pre-event and post-event followers across regular segments in terms of first principal component scores. This allowed us to capture how diversity of audience changed after the politicians appeared on the 'Mevzular Acik Mikrofon' show. Now, having same group of users, we will consider both PC1 and PC2 scores. For the show, we expect that guest politicians will attract more politically distant viewers. Let's assume that a guest politician has the PC1,PC2 scores $[a_1, b_1]$ and a new follower have the scores $[a_2, b_2]$ respectively. . To measure how politically distant this follower is from the guest politician, we calculated absolute distance between these two positions. Having these absolute distances, similar to previous density ratios analysis, we can now compare the distribution of distances of new followers to the guest politician itself.

Figure 4.7 reports the results of such analysis for Omer Faruk Gergerlioglu in terms of absolute distances. On the top we can see the distributions of new followers who started followed participants in the 15 days before and after the broadcast appearance, together with bootstrapped 95% confidence bands. Omer Faruk Gergerlioglu was the only politician that attended the show from HDP. Although Barış Atay once was a HDP member, he joined the Worker' Party of Turkey. Since HDP represent the one end of the spectrum in terms of both components, the participation of Gergerlioglu was important. When looking at the both dimensions, most prominent change observed in the Gergerlioglu case. The median distance of followers who joined after is nearly twice that of those who followed Gergerlioğlu before the broadcast. This difference is also evident in the Figure 4.7. Broadcast appears to have attracted more users who sit further away from Gergerlioglu's own estimated position

Another quite an interesting case observed regarding the participation of TİP member Barış Atay. As we mentioned before, the episode Barış Atay appeared has been a huge success and program became more popular. When we examined the follower composition change of Barış Atay's around the show date in terms of PC1 scores, we had observed that post-broadcast scores was relatively higher than the pre-broadcast scores. However, when we considered both dimensions, it can be seen that politically distant viewers are less likely to start following Barış Atay after his appearance. Result is shown in the Figure 4.8. Results for other participants shared in Appendix A.

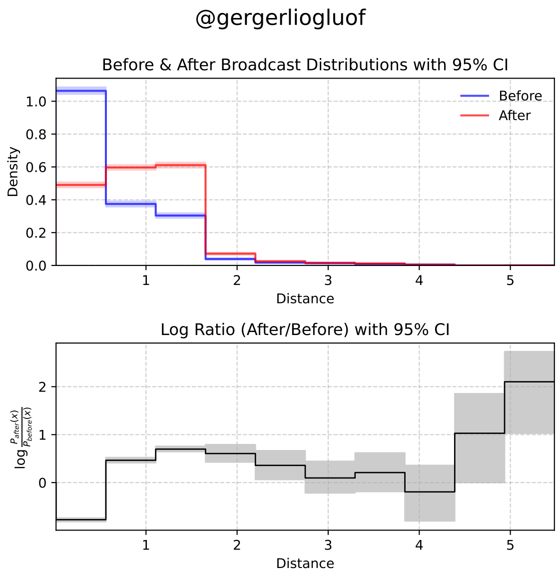

Figure 4.7 Top panel: Step-histograms of absolute distances for the new followers of Omer Faruk Gergerlioglu during the 15 days before (blue) and after (red) his broadcast appearance, with 95% bootstrap confidence bands shaded around each curve. Bottom panel: Log density ratio across the distances with 95% confidence intervals (gray).

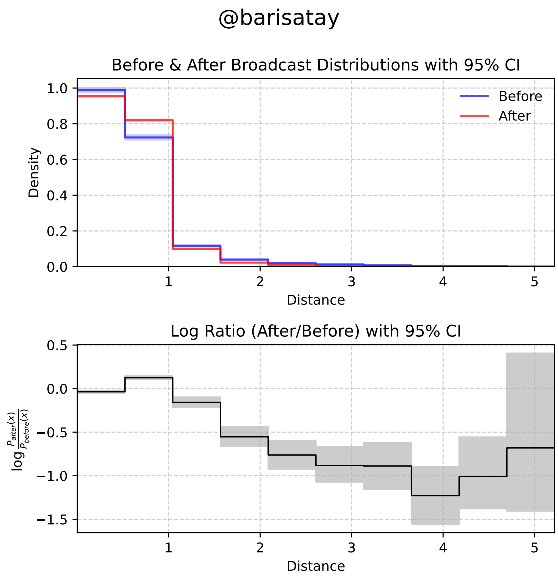

Figure 4.8 Top panel: Step-histograms of absolute distances for the new followers of Barış Atay during the 15 days before (blue) and after (red) his broadcast appearance, with 95% bootstrap confidence bands shaded around each curve. Bottom panel: Log density ratio across the distances with 95% confidence intervals (gray).

These results align with our second hypothesis stating online political debates contribute to the reduction of political polarization. Programs like Mevzular Acik Mikrofon provide platforms for engagements across ideological lines. As more followers with diverse political views start following participants, their exposure to different political information will increase.

4.3 Follower retention

Previous results presented evidence for our main hypothesis that political debates streamed online contribute to the reduction of political polarization. We now turn to the analysis of follower retention to further investigate the BabalaTV effect. To examine the lasting depolarizing impact of BabalaTV, we utilized our regularly collected social networks of political accounts.

Knowing the group of users that started following guest politicians within 30 days of their appearance on the program, we calculated ratio of these followers who continued to follow them until their next network snapshot. For reference, we identified three additional user groups: those who started following between the announcement and the show date, those who began following within 30 days before the participant's appearance, and those who followed the guest politician before 2023. This analysis allows us to assess the longer-term depolarization effect of BabalaTV.

In figure 4.9, we reported the results of follower retention analysis. We find that for majority of guest politicians, over %90 new followers who began following after their appearance on the program continued to follow them. Interestingly, a significant decrease in follower retention rates for @DrSinanOgan observed. Sinan Ogan was one of the key figures in the 2023 Turkish presidential election. After first round of election in which no candidate reached a %50 majority, he announced he would endorse Erdogan for second round. The announcement caused outrage, leading a significant portion of his follower base to unfollow him on Twitter in protest. Therefore, low rates in before, between and after columns for @DrSinanOgan can be explained in this way.

To gain deeper insights into audience dynamics, we integrated the bot scores of followers to their ideology scores across three distinct periods: (a) individuals who started following 30 days prior to the program, (b) individuals who started following within 30 days of the program's release, and (c) individuals who unfollowed

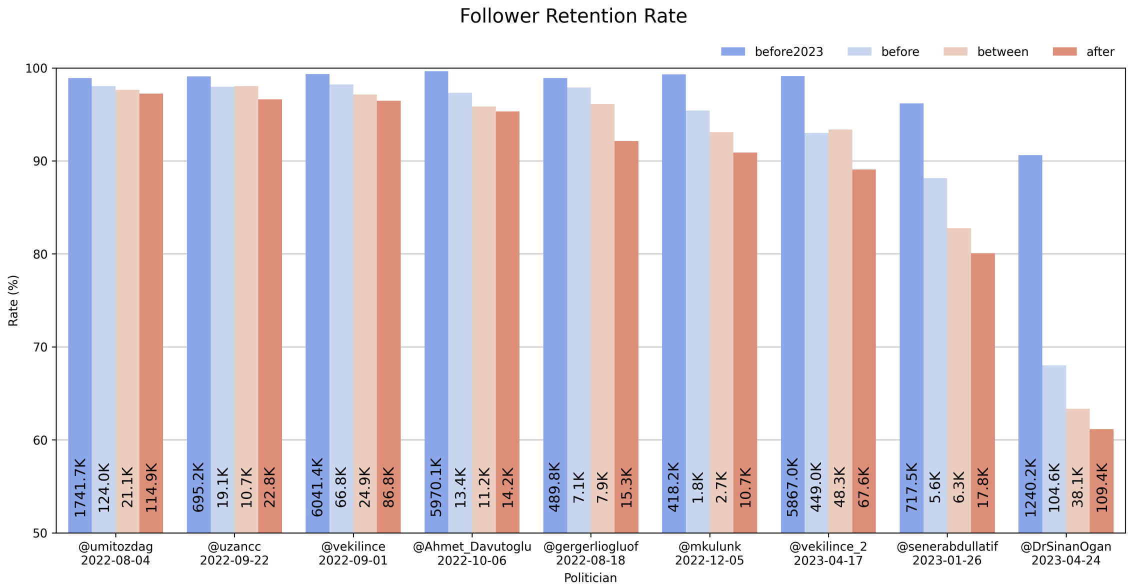

Figure 4.9 Follower retention rates for various politicians in four distinct periods: before 2023 , before the announcement, between the announcement and program, and after the program.

after initially following the politician following their appearance on the program. Previous studies showed that orchestrated activities were employed to manipulate the Turkish political landscape in social media Okuyucu (2023). More recently, Mugurtay, Duygu & Varol (2024) document how Twitter and Meta routinely dismantle state-linked influence campaigns originating in Turkey, highlighting the scale and persistence of coordinated manipulation on these platforms. Consequently, we treated bot activity as a potential confounder, letting us separate the organic audience.

The figure 4.10 presents joint density plots for several BabalaTV participants with lower follower retention rates in which x axis represent the ideology scores and y axis represent bot scores. The marginal distributions are displayed along the top and right sides. For @gergerliogluof, it is evident that users who started following 30 days prior, exhibit bot-like behaviors and they are concentrated within a narrow range of ideology scores. After Gergerlioglu appears on the program Mevzular Acik Mikrofon, density of followers expand in terms of ideology and bot score. He seems to attract more organic followers from a diverse political views. (c) shows that a slightly higher number of human-like followers unfollowed Gergerlioglu after initially following him.

In Figure 4.9, we provided an explanation for the low follower retention rates observed for Sinan Oğan. However, the findings for Abdullatif Şener were unexpected. Şener, who was a founding member of the Justice and Development Party (AKP) before joining the CHP, displayed relatively low follower retention. To further explore this outcome, we included a joint density plot for Şener Figure 4.10 that illustrates the ideology and bot score distributions of his followers before and after the observed retention declines. Notably, these distributions did not differ significantly, leaving the underlying causes of his low retention unclear.

Another interesting result concerns the participant @mkulunk (Metin Külünk). The second figure supports our earlier evidence presented in Figure 4.2, showing that a more ideologically diverse audience began following Külünk after his appearance on the show. Surprisingly, users who eventually unfollowed him tended to be positioned further to the left on the ideological spectrum than those who remained.

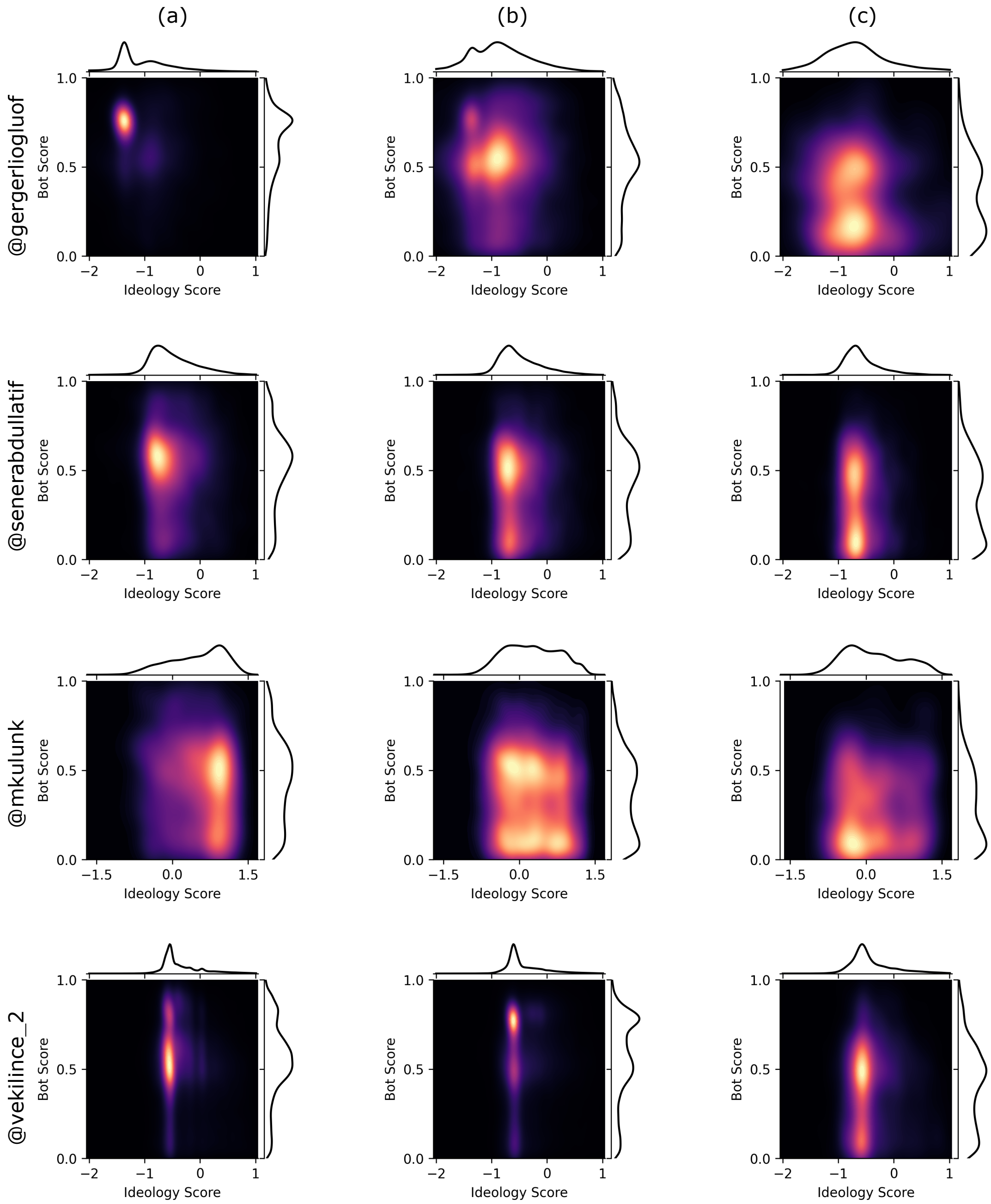

Figure 4.10 Joint distribution of ideology scores and bot scores of users across three distinct periods: (a) 30 days prior to the program, (b) within 30 days following the program's release, and (c) users who unfollowed the politician after initially following them.

4.4 Youtube

Sentiment Polarization among Common Commenters

In the political science literature, scholars study polarization in two dimensions: ideological and affective. Ideological polarization focuses on how opinions are distributed within a society. As more individuals adopt extreme viewpoints, ideological polarization increases. Affective polarization, on the other hand, examines the growing distrust and hostility toward out-groups (Iyengar et al., 2019). A common method for measuring affective polarization is the "feeling thermometer," which calculates the difference between in-group favoritism and out-group animosity. To examine the polarizing effects of content on YouTube, we apply a similar approach by analyzing how audience sentiments differ toward various politicians who appeared on Mevzular Açık Mikrofon.

To do so, we identified commenters who left comments on multiple episodes of Mevzular Açık Mikrofon. For each pair of guest politicians, we calculated the difference in the average sentiment of comments. Figure 4.11 demonstrates the sentiment polarization among these shared commenters. Based on the pairwise sentiment scores, no significant differences were detected. These findings align with our earlier observations.

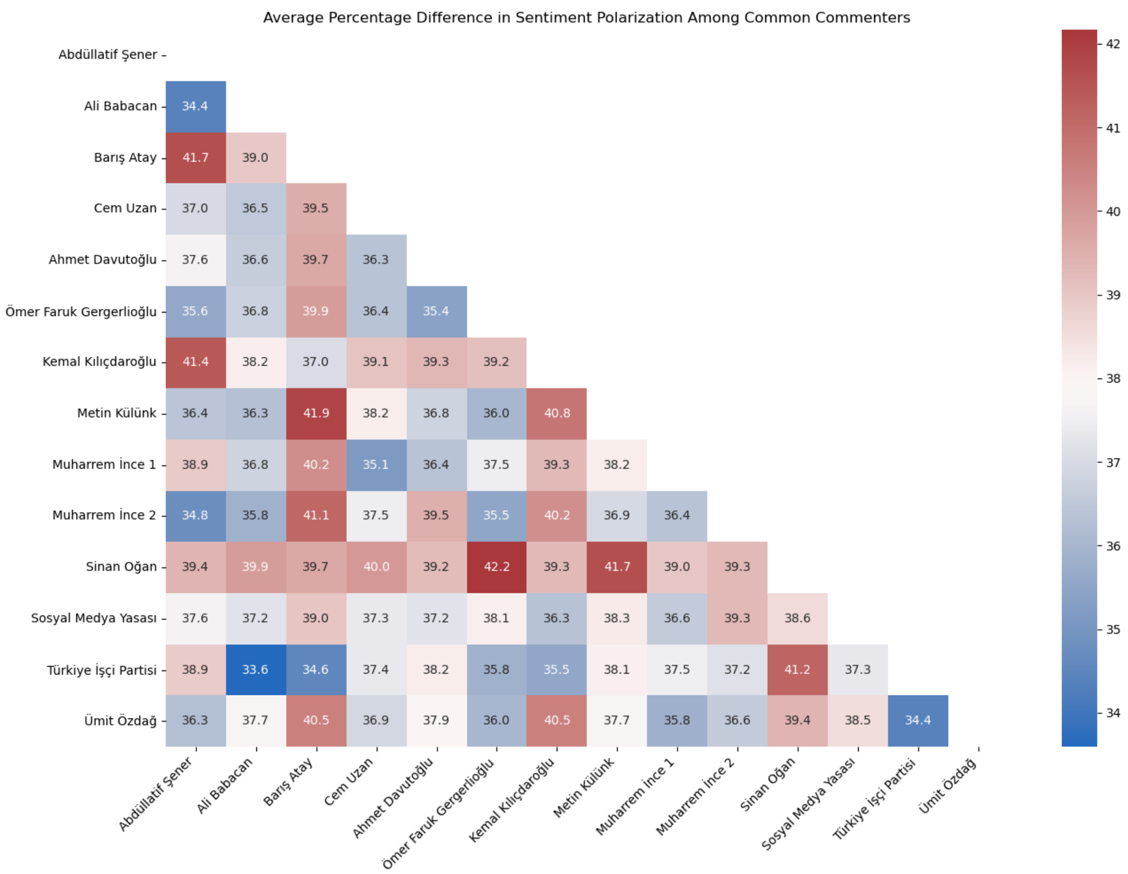

Figure 4.11 Sentiment polarization among common commenters of Mevzular Acik Mikrofon

Discourse Analysis

The use of language in speeches and social media can reveal characteristic words or phrases associated with political entities (Monroe, Colaresi & Quinn, 2008). To analyze the linguistic variation in episodes of Mevzular Acik Mikrofon, we prepared a scatterplot where the x axis represents the relative frequencies of terms (logged) in politician speech and the y axis represents the relative frequencies of terms (logged) in the comment section of the video of YouTube Figure 4.12. Words with higher y-axis values are more frequently used in the corresponding speech compared to other episodes, while words positioned further to the right on the x-axis are more frequently used in the corresponding comment section compared to comments on other episodes. Highly characteristic words located in the upper right quadrant. The size of each point reflects the word count, and the color represents the average sentiment of comments in which the word appears.

For comparison, we analyzed three guest politicians from the BabalaTV show: a presidential candidate from the Memleket party (Muharrem İnce), a presidential candidate representing the far-right ATA Alliance (Sinan Oğan), and a politician from the far-left TKP (Barış Atay). One notable finding is the overwhelming negative sentiment associated with Muharrem nce's second appearance on the show (Figure 4.12(a)). Most words related to his appearance are shaded in darker reds, indicating a predominance of negative sentiment. This is not surprising since his second appearance on the show is widely criticized. The trailer released for his appearance was full of moments in which he adopted an aggressive attitude towards the audience. In contrast, the appearances of Sinan Oğan and Barış Atay were received more positively, with relatively fewer negative sentiments expressed in the corresponding comments sections.

Immigration emerged as a significant topic of discussion, reflecting its prominence in Turkish politics across the ideological spectrum. The Syrian civil war, which began in 2011, led to a massive wave of immigration into neighboring countries, including Türkiye. Combined with a worsening economic situation, immigration has become a central issue in Turkish political discourse, fueling the rise of far-right parties such as the Zafer Party. This is evident in our analysis, as terms related to immigration frequently appeared in speeches and comment sections.

It is apparent from Figure 4.12(c) that terms like "kapitalist", "sosyalist", and "isci" are strongly associated with Barış Atay since they have high log ratios on both axes. This aligns with his leftist political stance, as these terms reflect key elements of his ideological perspective.

On the other hand, terms like "terör," "hdp," and "pkk" are represented by larger circles, showing that they were the dominant themes driving the discourse. In addition, these words are also shaded in darker red, reflecting highly negative sentiment. This finding may help us to understand the topics that have the potential to polarize the audience.

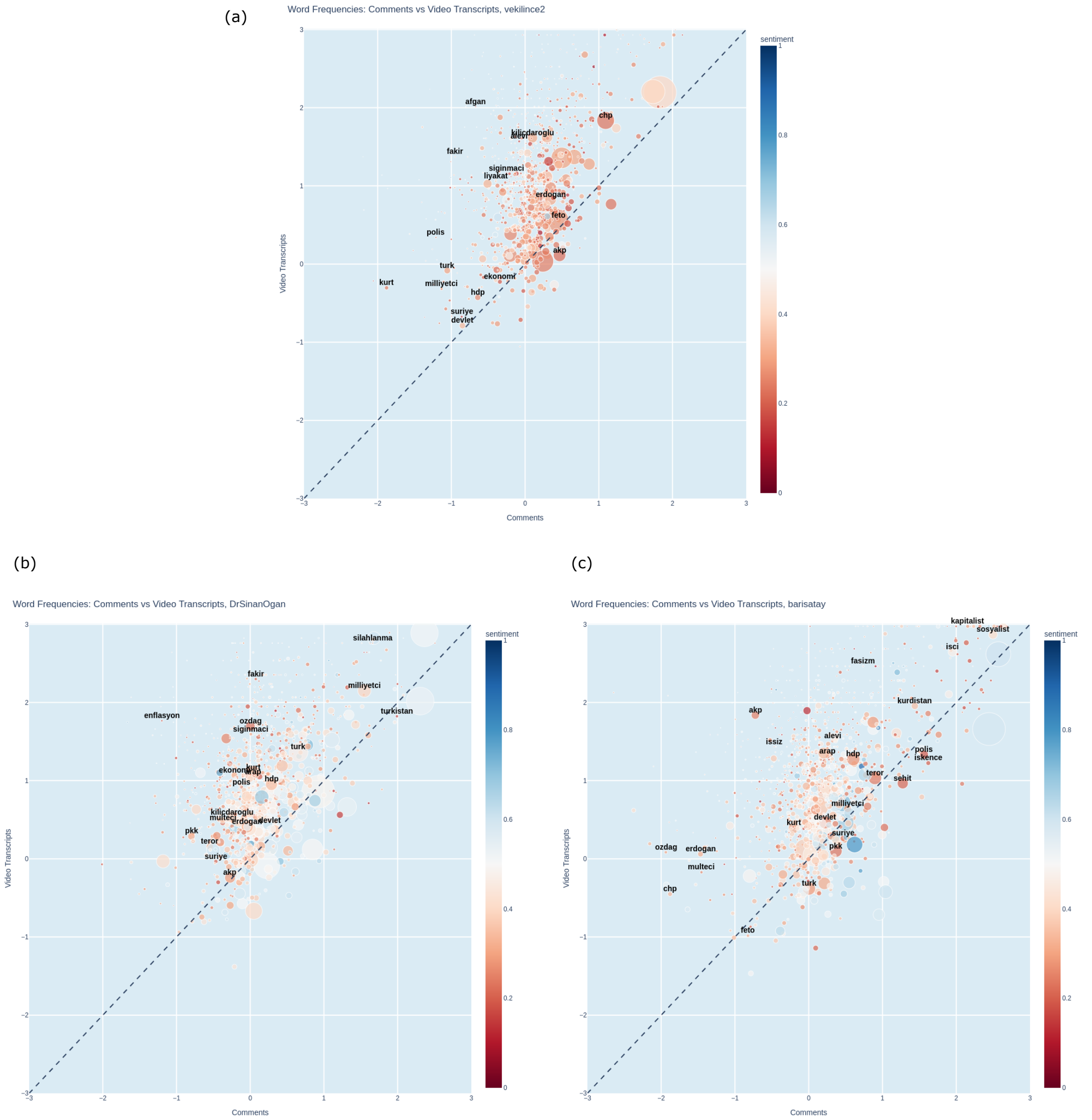

Figure 4.12 Scatterplot comparing the relative frequencies of words of video transcript (y-axis) and YouTube comments (x-axis) from Mevzular Açık Mikrofon

5. Conclusion

Digital media has transformed political communication and participation. It offers new channels for public engagement while raising concerns about echo chambers and polarization. In countries like Turkey, where government control over mainstream media is significant, platforms such as YouTube play a crucial role in providing alternative spaces for political dialogue.

Our work revealed three main findings. First, online debate shows, particularly BabalaTV-Mevzular Acik Mikrofon, had a significant impact on the online public outreach trends of guest politicians. Using the #secim2023 dataset, we demonstrated that after politicians appeared on the show, they attracted more followers and online discussion on Twitter. This increased activity was also reflected in Google Trends and Wikipedia. Interestingly, similar effects were not observed for other online political discussion shows on YouTube. With its challenging and critical format, which allows direct audience participation in discussions, the show proved to be highly successful in the lead-up to the 2023 Türkiye presidential election. These results are encouraging as they suggest that online debate shows can serve as valuable platforms for politicians to enhance their visibility and engagement with the public. By leveraging such shows as part of their campaign strategies, politicians can reach a broader audience, foster meaningful discussions, and build stronger connections with voters in the digital space.

Second, we highlighted how the follower composition of guest politicians changes around the time they appear on the show. By analyzing follow-time data and ideological placement estimates, we observed that politicians such as Metin Külünk and Barış Atay attracted followers with more diverse ideological backgrounds. As people with differing political views start following these politicians, they are more likely to be exposed to information that challenges their existing beliefs, potentially contributing to a reduction in political polarization. These findings align with our second hypothesis, which proposed that online political discussion shows can help reduce polarization. However, caution must be applied as the second finding cannot be generalized to all BabalaTV participants. Variation in the change in follower ideological composition further needs to be examined in future studies.

Third, follower retention rates analysis suggests that the depolarization impact of BabalaTV does not go away quickly, demonstrated by over 90 percent retention rates for the vast majority of guest politicians.

Recently, following Elon Musk's acquisition of Twitter, there was a major change in the platform's API policy. The company stopped providing the academic API, which previously offered free data access to researchers studying social media. However, our method remains applicable to other platforms that provide a chronological list of followers with their account creation dates (Zouzou & Varol, 2024) for estimating follow times, as well as lists of followers and friends for estimating ideology scores.

This study provides valuable insights into the impact of online broadcasting on political behavior, emphasizing the importance of alternative media in politically restrictive environments.

BIBLIOGRAPHY

Adamic, L. A. & Glance, N. (2005). The political blogosphere and the 2004 us election: divided they blog. In *Proceedings of the 3rd international workshop on Link discovery*, (pp. 36–43).

Ahmed, S. & Skoric, M. M. (2014). My name is khan: the use of twitter in the campaign for 2013 pakistan general election. In *2014 47th Hawaii International Conference on System Sciences*, (pp. 2242–2251). IEEE.

Altinok, D. (2023). A diverse set of freely available linguistic resources for Turkish. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, (pp. 13739–13750)., Toronto, Canada. Association for Computational Linguistics.

Arceneaux, K. & Johnson, M. (2010). Does media fragmentation produce mass polarization? selective exposure and a new era of minimal effects. *Selective Exposure and a New Era of Minimal Effects*.

Arceneaux, K., Johnson, M., & Murphy, C. (2012). Polarized political communication, oppositional media hostility, and selective exposure. *The Journal of Politics*, *74*(1), 174–186.

Aydın Düzgit, S. (2019). *The Islamist-Secularist divide and Turkey's descent into severe polarization*. Brookings Institution Press.

Bakshy, E., Messing, S., & Adamic, L. A. (2015). Exposure to ideologically diverse news and opinion on facebook. *Science*, *348*(6239), 1130–1132.

Barberá, P. (2014). How social media reduces mass political polarization. evidence from germany, spain, and the us. *Job Market Paper, New York University*, *46*, 1–46.

Barberá, P. (2015). Birds of the same feather tweet together: Bayesian ideal point estimation using twitter data. *Political analysis*, *23*(1), 76–91.

Barberá, P., Jost, J. T., Nagler, J., Tucker, J. A., & Bonneau, R. (2015). Tweeting from left to right: Is online political communication more than an echo chamber? *Psychological science*, *26*(10), 1531–1542.

Baxter, G. & Marcella, R. (2012). Does scotland 'like'this? social media use by political parties and candidates in scotland during the 2010 uk general election campaign. *Libri*, *62*(2), 109–124.

Boukes, M. & Trilling, D. (2017). Political relevance in the eye of the beholder: Determining the substantiveness of tv shows and political debates with twitter data. *First Monday*.

Boxell, L., Gentzkow, M., & Shapiro, J. M. (2017). Is the internet causing political polarization? evidence from demographics. Technical report, National Bureau of Economic Research.

Bulut, E. & Yörük, E. (2017). Mediatized populisms| digital populism: Trolls and political polarization of twitter in turkey. *International Journal of Communication*, *11*, 25.

Çarkoğlu, A. (2012). Economic evaluations vs. ideology: Diagnosing the sources of electoral change in turkey, 2002–2011. *Electoral Studies*, *31*(3), 513–521.

Cinelli, M., De Francisci Morales, G., Galeazzi, A., Quattrociocchi, W., & Starnini, M. (2021). The echo chamber effect on social media. *Proceedings of the Na-*

tional Academy of Sciences, *118*(9), e2023301118.
Conover, M., Ratkiewicz, J., Francisco, M., Gonçalves, B., Menczer, F., & Flammini, A. (2011). Political polarization on twitter. In *Proceedings of the international aaai conference on web and social media*, volume 5, (pp. 89–96).
Dahl, R. A. (2005). What political institutions does large-scale democracy require? *Political Science Quarterly*, *120*(2), 187–197.
Devlin, J. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*.
Djerf-Pierre, M., Lindgren, M., & Budinski, M. A. (2019). The role of journalism on youtube: audience engagement with" superbug" reporting. *Media and Communication*, *7*(1), 235–247.
Douai, A. (2019). Online activism and the arab public sphere: The case of youtube and human rights campaigns. In *Police Science: Breakthroughs in Research and Practice* (pp. 324–339). IGI Global.
Ekman, M. (2014). The dark side of online activism: Swedish right-wing extremist video activism on youtube. *MedieKultur: Journal of media and communication research*, *30*(56), 21–p.
English, K., Sweetser, K. D., & Ancu, M. (2011). Youtube-ification of political talk: An examination of persuasion appeals in viral video. *American Behavioral Scientist*, *55*(6), 733–748.
Erdogan, E. (2016). Turkey: Divided we stand. *On Turkey*, *118*, 1–4.
Erdoğan, E. & Uyan-Semerci, P. (2018). *Fanusta diyaloglar: Türkiye'de kutuplaşmanın boyutları*. İstanbul Bilgi Üniversitesi Yayınları.
Esen, B. & Gumuscu, S. (2016). Rising competitive authoritarianism in turkey. *Third World Quarterly*, *37*(9), 1581–1606.
Esen, B. & Gumuscu, S. (2018). The perils of "turkish presidentialism". *Review of Middle East Studies*, *52*(1), 43–53.
Fiorina, M. P. & Abrams, S. J. (2008). Political polarization in the american public. *Annu. Rev. Polit. Sci.*, *11*(1), 563–588.
Fiorina, M. P., Abrams, S. J., & Pope, J. (2004). *Culture war? The myth of a polarized America*. Longman.
García-Marín, J. (2021). Youtube and traditional media: Polarization in the catalan political conflict. In *Digitalization of Democratic Processes in Europe: Southern and Central Europe in Comparative Perspective* (pp. 31–41). Springer.
Gaughan, C. (2024). Estimating ideal points of british mps through their social media followership. *British Journal of Political Science*, *54*(4), 1506–1518.
Gentzkow, M. (2006). Television and voter turnout. *The Quarterly Journal of Economics*, *121*(3), 931–972.
Gondwe, G. (2017). Are late night tv shows in the polarizing society? examining the ambivalence of new version of political partisanship in the united states? *Global Media Journal*, *15*(29), 1–6.
Griffen, S. (2019). A glimpse of press freedom in turkey. *British Journalism Review*, *30*(3), 37–41.
Grover, P., Kar, A. K., Dwivedi, Y. K., & Janssen, M. (2019). Polarization and acculturation in us election 2016 outcomes–can twitter analytics predict changes in voting preferences. *Technological Forecasting and Social Change*, *145*, 438–460.
Hanson, G. L., Haridakis, P. M., & Sharma, R. (2011). Differing uses of youtube

during the 2008 us presidential primary election. *Electronic News*, *5*(1), 1–19.
Hayes, D. (2009). Has television personalized voting behavior? *Political Behavior*, *31*, 231–260.
Hohmann, M., Devriendt, K., & Coscia, M. (2023). Quantifying ideological polarization on a network using generalized euclidean distance. *Science Advances*, *9*(9), eabq2044.
Hosseinmardi, H., Ghasemian, A., Clauset, A., Mobius, M., Rothschild, D. M., & Watts, D. J. (2021). Examining the consumption of radical content on youtube. *Proceedings of the National Academy of Sciences*, *118*(32), e2101967118.
House, F. (2017). Freedom of the press 2017.
Intyaswati, D., Intityaswi, D., Maryani, E., Venus, A., & Sugiana, D. (2019). Political expression on youtube during the 2019 presidential election campaign with uses and dependency perspective. In *International Conference on Democratisation in Southeast Asia (ICDeSA 2019)*, (pp. 36–40). Atlantis Press.
Irak, D. (2016). A close-knit bunch: Political concentration in turkey's anadolu agency through twitter interactions. *Turkish Studies*, *17*(2), 336–360.
Iyengar, S., Lelkes, Y., Levendusky, M., Malhotra, N., & Westwood, S. J. (2019). The origins and consequences of affective polarization in the united states. *Annual review of political science*, *22*(1), 129–146.
Iyengar, S., Sood, G., & Lelkes, Y. (2012). Affect, not ideology: A social identity perspective on polarization. *Public opinion quarterly*, *76*(3), 405–431.
Jungherr, A. (2016). Twitter use in election campaigns: A systematic literature review. *Journal of information technology & politics*, *13*(1), 72–91.
Kalsnes, B., Krumsvik, A. H., & Storsul, T. (2014). Social media as a political backchannel: Twitter use during televised election debates in norway. *Aslib journal of information management*.
Lauka, A., McCoy, J., & Firat, R. B. (2018). Mass partisan polarization: Measuring a relational concept. *American behavioral scientist*, *62*(1), 107–126.
Ledwich, M. & Zaitsev, A. (2019). Algorithmic extremism: Examining youtube's rabbit hole of radicalization. *arXiv preprint arXiv:1912.11211*.
Levendusky, M. (2009). *The partisan sort: How liberals became Democrats and conservatives became Republicans*. University of Chicago Press.
Levitsky, S. & Way, L. A. (2002). Elections without democracy: The rise of competitive authoritarianism. *Journal of democracy*, *13*(2), 51–65.
Maier, J. & Faas, T. (2011). "miniature campaigns" in comparison: the german televised debates, 2002–09. *German Politics*, *20*(1), 75–91.
Mardin, Ş. (1973). Center-periphery relations: A key to turkish politics? *Daedalus*, 169–190.
McKinney, M. S. & Rill, L. A. (2009). Not your parents' presidential debates: Examining the effects of the cnn/youtube debates on young citizens' civic engagement. *Communication Studies*, *60*(4), 392–406.
Meeder, B., Karrer, B., Sayedi, A., Ravi, R., Borgs, C., & Chayes, J. (2011). We know who you followed last summer: inferring social link creation times in twitter. In *Proceedings of the 20th international conference on World wide web*, (pp. 517–526).
Metin, O. F. & Morales, P. R. (2022). Tweeting apart: Democratic backsliding, new party cleavage and changing media ownership in turkey. In *8th International*

Conference on Computational Social Science IC2S2.

Mill, J. S. (1998). *On liberty and other essays*. Oxford University Press, USA.

Monroe, B. L., Colaresi, M. P., & Quinn, K. M. (2008). Fightin'words: Lexical feature selection and evaluation for identifying the content of political conflict. *Political Analysis*, *16*(4), 372–403.

Mugurtay, N., Duygu, U., & Varol, O. (2024). Politics and propaganda on social media: How twitter and meta moderate state-linked information operations. *arXiv preprint arXiv:2401.02095*.

Munger, K. & Phillips, J. (2022). Right-wing youtube: A supply and demand perspective. *The International Journal of Press/Politics*, *27*(1), 186–219.

Najafi, A., Mugurtay, N., Zouzou, Y., Demirci, E., Demirkiran, S., Karadeniz, H. A., & Varol, O. (2024). First public dataset to study 2023 turkish general election. *Scientific Reports*, *14*(1), 8794.

Najafi, A. & Varol, O. (2024). Turkishbertweet: Fast and reliable large language model for social media analysis. *Expert Systems with Applications*, *255*, 124737.

Ogan, C. & Varol, O. (2017). What is gained and what is left to be done when content analysis is added to network analysis in the study of a social movement: Twitter use during gezi park. *Information, Communication & Society*, *20*(8), 1220–1238.

Okuyucu, A. F. (2023). *Understanding Manipulative Actions And Political Language On Twitter: Exploring Trending Topics And The 2023 Turkish Presidential Election*. PhD thesis, Sabancı University.

Pariser, E. (2011). *The filter bubble: What the Internet is hiding from you*. penguin UK.

Patterson, T. E. & McClure, R. D. (1976). Television and the less-interested voter: The costs of an informed electorate. *The Annals of the American Academy of Political and Social Science*, *425*(1), 88–97.

Pierre, A. (2023). Turkish elections: 'open mic' youtube show is shaping how young people think about politics.

Saka, E. (2016). Siyasi trollük örneği olarak aktroller. *Birikim, C*, *322*, 17–21.

Schweter, S. (2020). Berturk - bert models for turkish.

Somer, M. (2019). Turkey: The slippery slope from reformist to revolutionary polarization and democratic breakdown. *The ANNALS of the American Academy of Political and Social Science*, *681*(1), 42–61.

Sørensen, R. J. (2019). The impact of state television on voter turnout. *British Journal of Political Science*, *49*(1), 257–278.

Strömbäck, J., Falasca, K., & Kruikemeier, S. (2018). The mix of media use matters: Investigating the effects of individual news repertoires on offline and online political participation. *Political Communication*, *35*(3), 413–432.

Sunstein, C. (2001). *Republic. com*. Princeton University Press.

Toros, E. (2015). Negative campaigning in turkish elections. *Turkish Studies*, *16*(4), 487–509.

Toros, S. & Toros, E. (2022). Social media use and political participation: the turkish case. *Turkish Studies*, 1–24.

Varol, O., Ferrara, E., Ogan, C. L., Menczer, F., & Flammini, A. (2014). Evolution of online user behavior during a social upheaval. In *Proceedings of the 2014 ACM conference on Web science*, (pp. 81–90).

Vesnic-Alujevic, L. & Van Bauwel, S. (2014). Youtube: A political advertising tool?

a case study of the use of youtube in the campaign for the european parliament elections. *Journal of Political Marketing*, *13*(3), 195–212.

Yaman, A. (2014). The gezi park protests: The impact on freedom of expression in turkey. *PEN International*.

Yesil, B. (2014). Press censorship in turkey: Networks of state power, commercial pressures, and self-censorship. *Communication, Culture & Critique*, *7*(2), 154–173.

Yesil, B. (2021). Social media manipulation in turkey: Actors, tactics, targets. In *The Routledge Companion to Media Disinformation and Populism* (pp. 386–396). Routledge.

Yildirim, S. (2024). Fine-tuning transformer-based encoder for turkish language understanding tasks.

Zouzou, Y. & Varol, O. (2024). Unsupervised detection of coordinated fake-follower campaigns on social media. *EPJ Data Science*, *13*(1), 62.

APPENDIX A

Table A.1 Broadcast metrics for 'Liderler Özel' on the YouTube channel 'SÖZCÜ Televizyonu' (* in Thousands).

Participant	Party Affil.	Broadcast	Views*	Comments
Erkan Baş	TİP	10/04/2023	118.2	150
Muharrem İnce	MP	18/04/2023	122.4	760
Kemal Kılıçdaroğlu	CHP	26/04/2023	133.3	191
Muharrem İnce	MP	03/05/2023	216.8	1512
Ali Babacan	DP	08/05/2023	73.9	42

Table A.2 Broadcast metrics for 'Teke Tek' on the YouTube channel 'Habertürk TV' (* in Thousands).

Participant	Party Affil.	Broadcast	Views*	Comments
Mithat Sancar	HDP	06/03/2023	47.0	108
Sinan Oğan	ATA	13/03/2023	361.3	1440
Erkan Baş	TİP	14/03/2023	201.7	370
Muharrem İnce	MP	21/03/2023	1025.0	4118
Ali Babacan	DP	26/04/2023	156.1	216
Meral Akşener	İYİ	02/05/2023	87.9	130
Sinan Oğan	ATA	12/05/2023	160.0	745

Table A.3 Broadcast metrics for 'Uğur Dündar ile Haftanın Panoraması' on the YouTube channel 'TV100' (* in Thousands).

Participant	Party Affil.	Broadcast	Views*	Comments
Kemal Kılıçdaroğlu	CHP	14/01/2023	71.0	714
Temel Karamollaoğlu	SP	26/02/2023	24.6	180
Meral Akşener	İYİ	18/03/2023	127.0	450
Erkan Baş	TİP	02/04/2023	333.4	700
Muharrem İnce	MP	05/04/2023	913.0	2780

Table A.4 Broadcast metrics for 'Liderler FOX'ta' on the YouTube channel 'NOW Haber' (* in Thousands).

Participant	Party Affil.	Broadcast	Views*	Comments
Meral Akşener	İYİ	06/05/2023	60.0	90
Kemal Kılıçdaroğlu	CHP	13/05/2023	131.0	410
Ekrem İmamoğlu	CHP	20/05/2023	170.0	630

Table A.5 Broadcast metrics for various joint broadcasts featuring Recep Tayyip Erdoğan on YouTube (* in Thousands).

Channel	Program	Broadcast	Views*	Comments
TRT Haber	Cumhurbaşkanı Özel Yayın	01/02/2023	87.8	300
24 TV	Cumhurbaşkanı Erdoğan Özel	05/04/2023	8.0	49
CNN TÜRK	Cumhurbaşkanı Özel Yayın	12/04/2023	86.2	225
TRT Haber	Cumhurbaşkanı Özel Yayın	19/04/2023	46.7	155
ÜLKE TV	Cumhurbaşkanı Seçim Özel	25/04/2023	37.2	145
TRT Haber	Cumhurbaşkanı Özel Yayın	12/05/2023	56.5	113
CNN TÜRK	Cumhurbaşkanı Özel Yayın	25/05/2023	154.0	592

Public Outreach Indicators

BabalaTV - Mevzular Açık Mikrofon

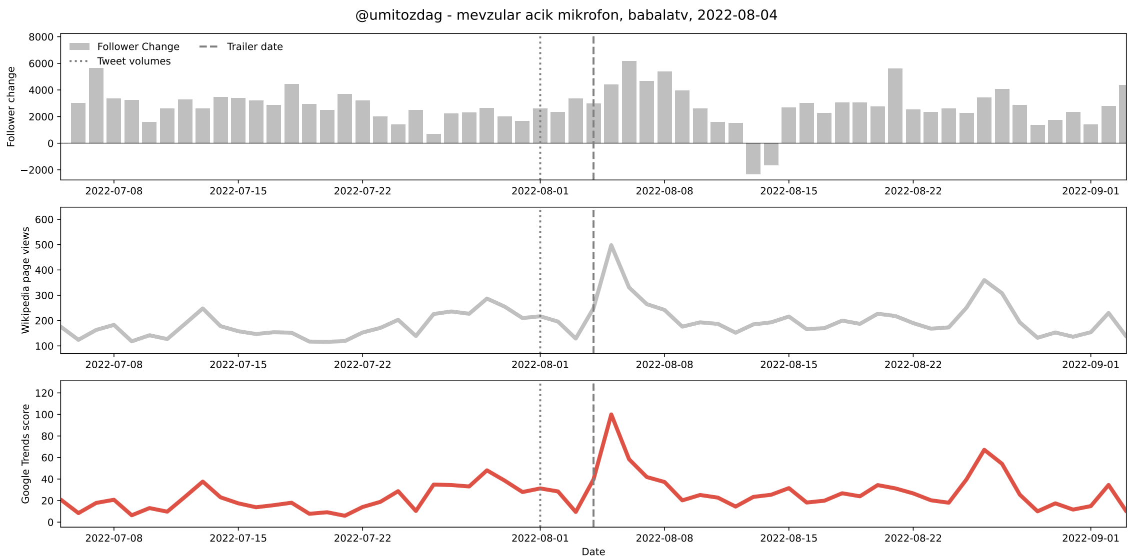

Figure A.1 Effect of participating the BabalaTV show “Mevzular Açık Mikrofon”, Ümit Özdağ .

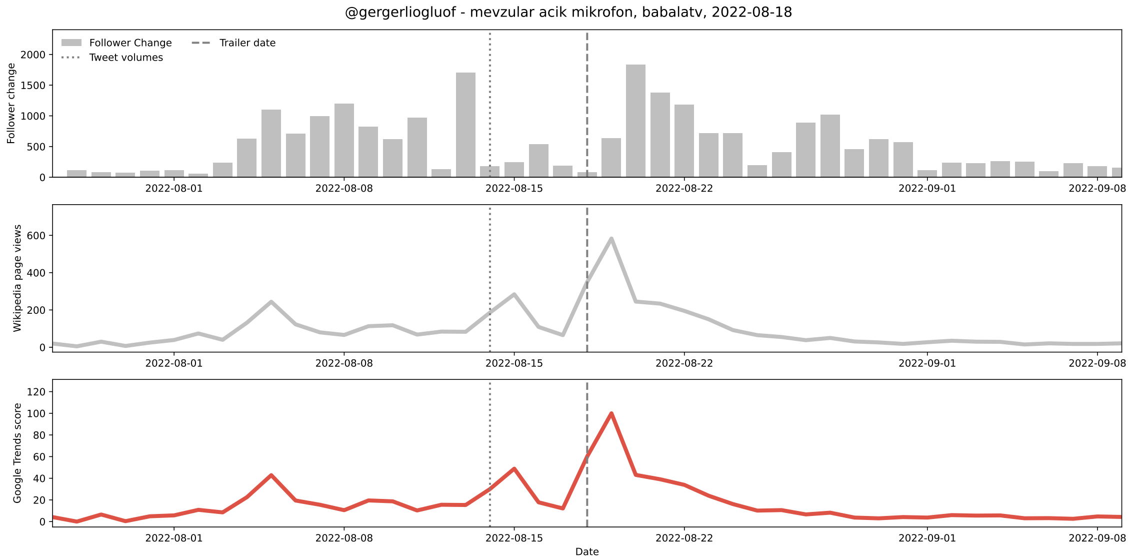

Figure A.2 Effect of participating the BabalaTV show “Mevzular Açık Mikrofon”, Ömer Faruk Gergerlioğlu .

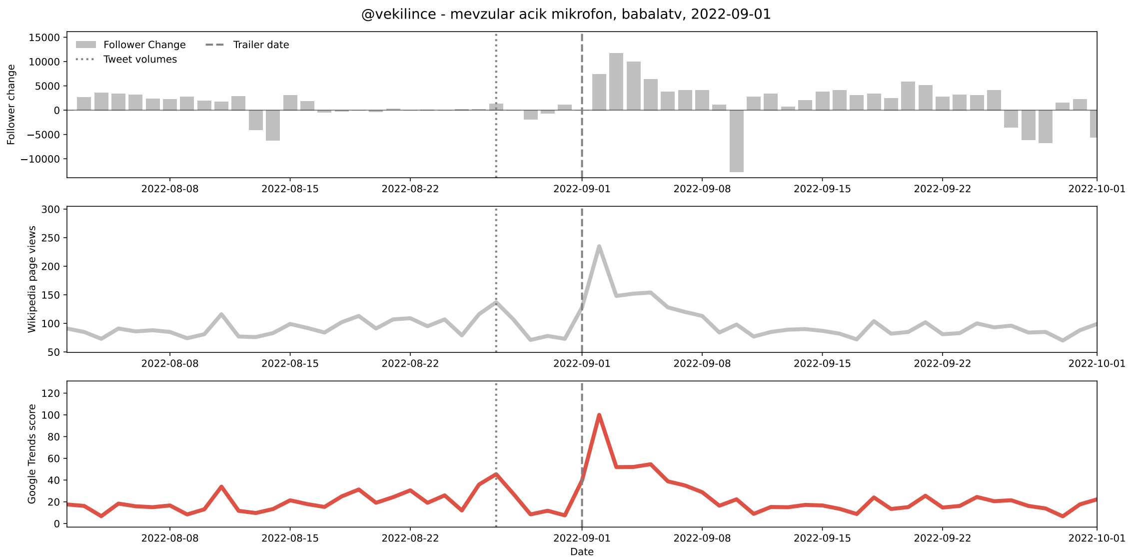

Figure A.3 Effect of participating the BabalaTV show “Mevzular Açık Mikrofon”, Muharrem Ince, 1st appearance .

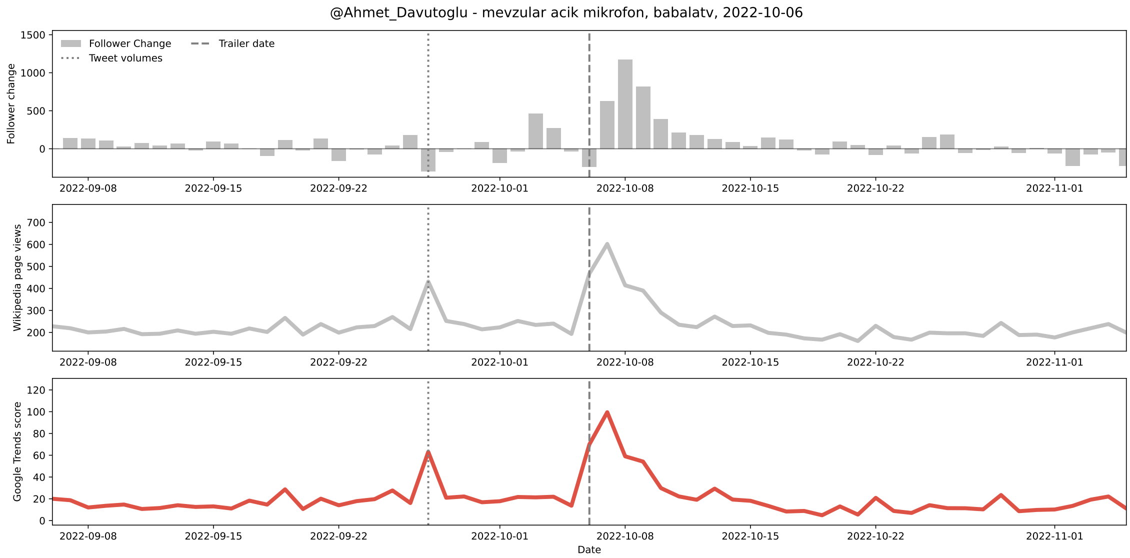

Figure A.4 Effect of participating the BabalaTV show “Mevzular Açık Mikrofon”, Ahmet Davutoğlu .

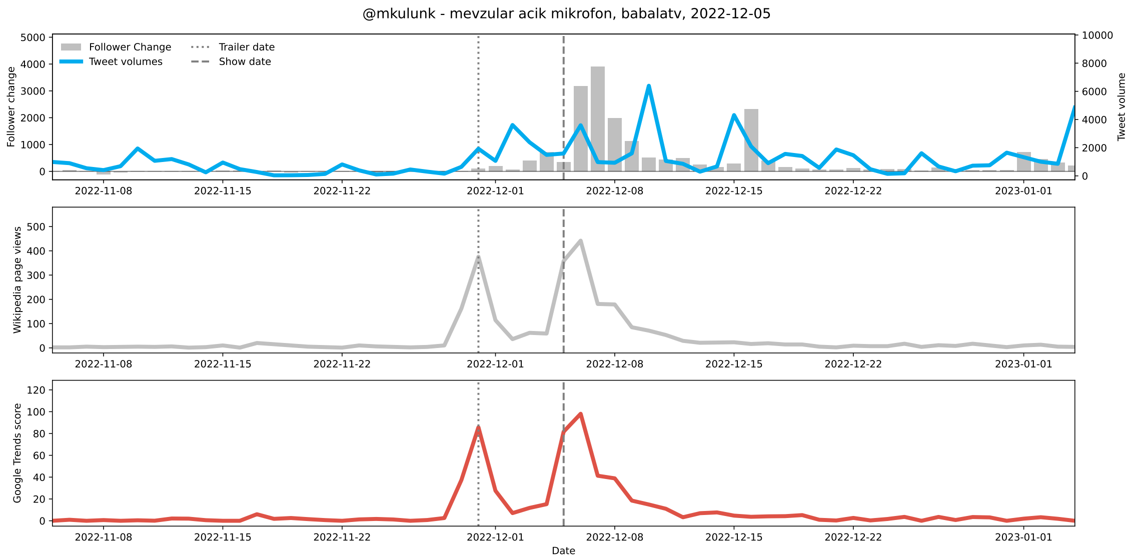

Figure A.5 Effect of participating the BabalaTV show “Mevzular Açık Mikrofon”, Metin Külünk .

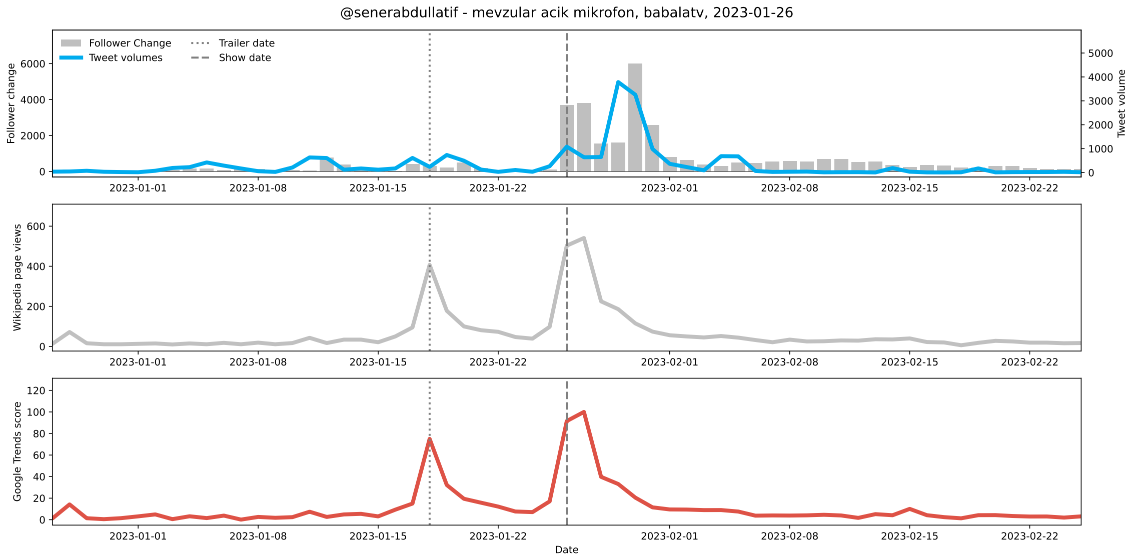

Figure A.6 Effect of participating the BabalaTV show “Mevzular Açık Mikrofon”, Abdullatif Şener .

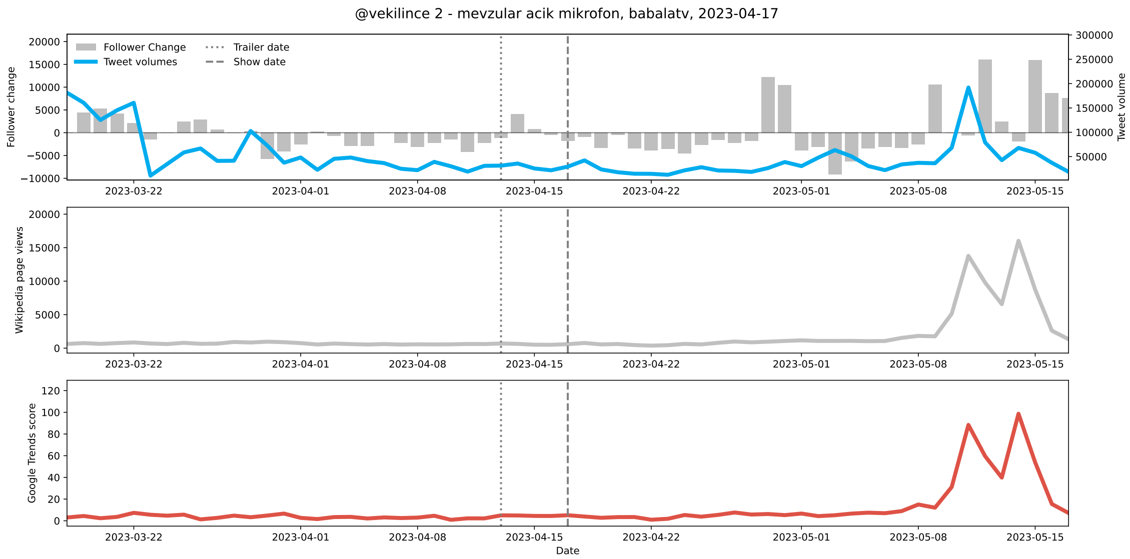

Figure A.7 Effect of participating the BabalaTV show “Mevzular Açık Mikrofon”, Muharrem İnce, 2nd appearance .

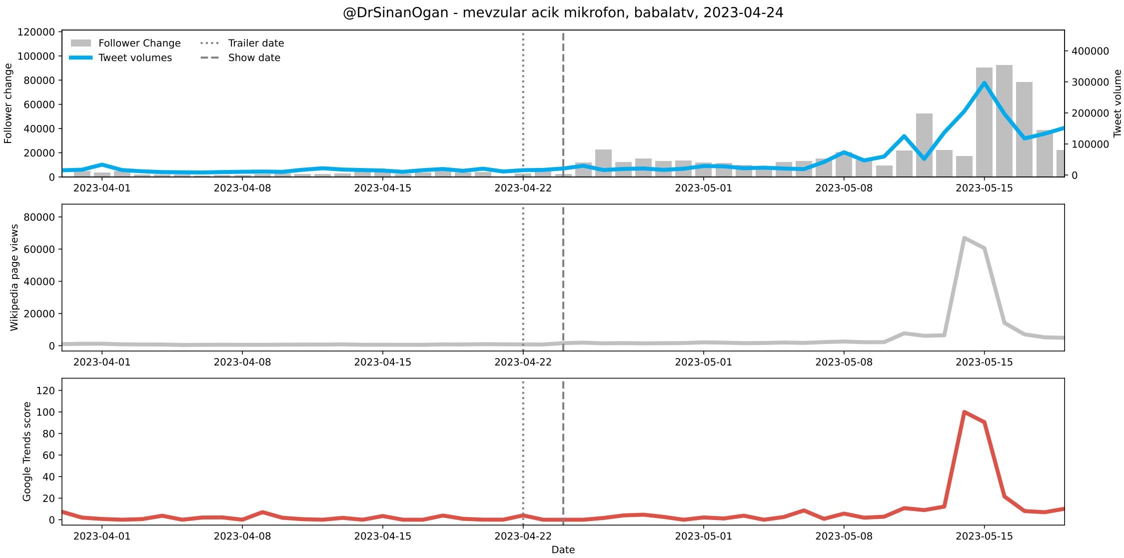

Figure A.8 Effect of participating the BabalaTV show “Mevzular Açık Mikrofon”, Sinan Oğan .

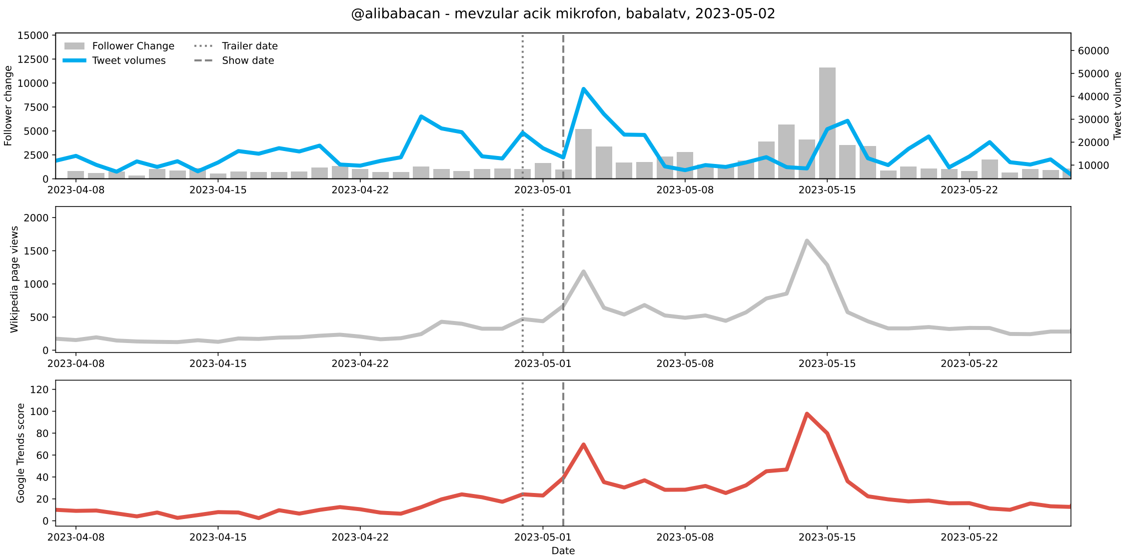

Figure A.9 Effect of participating the BabalaTV show “Mevzular Açık Mikrofon”, Ali Babacan .

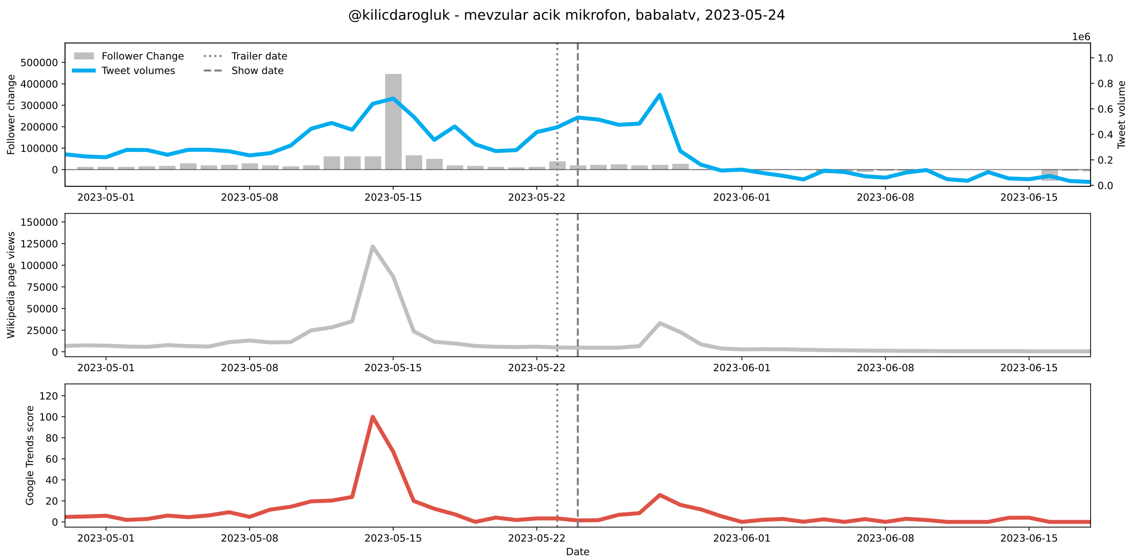

Figure A.10 Effect of participating the BabalaTV show “Mevzular Açık Mikrofon”, Kemal Kılıçdaroğlu .

Habertürk - Teke Tek

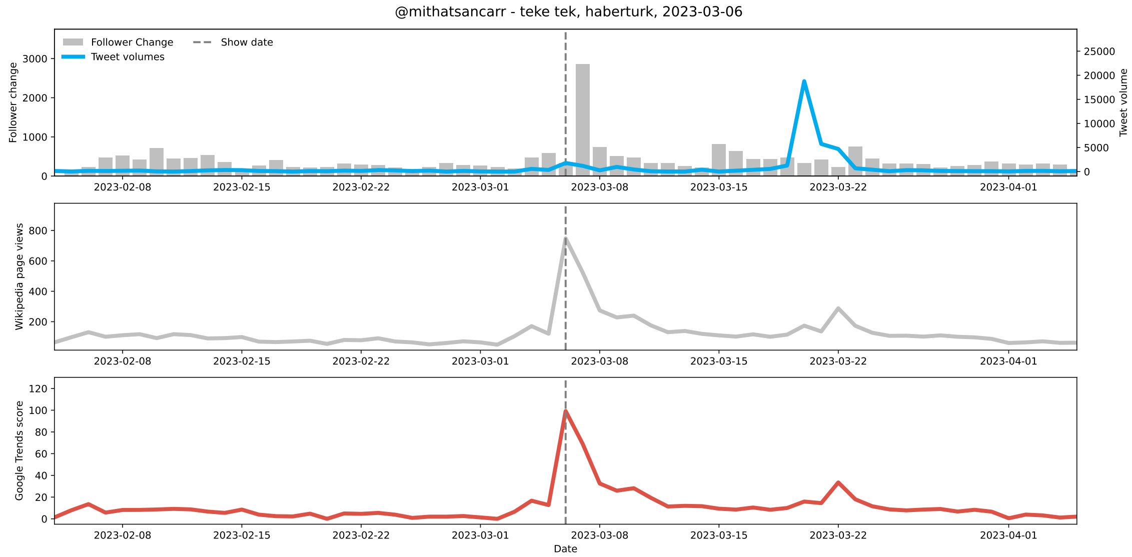

Figure A.11 Effect of participating the Habertürk show “Teke Tek”, Mithat Sancar
.

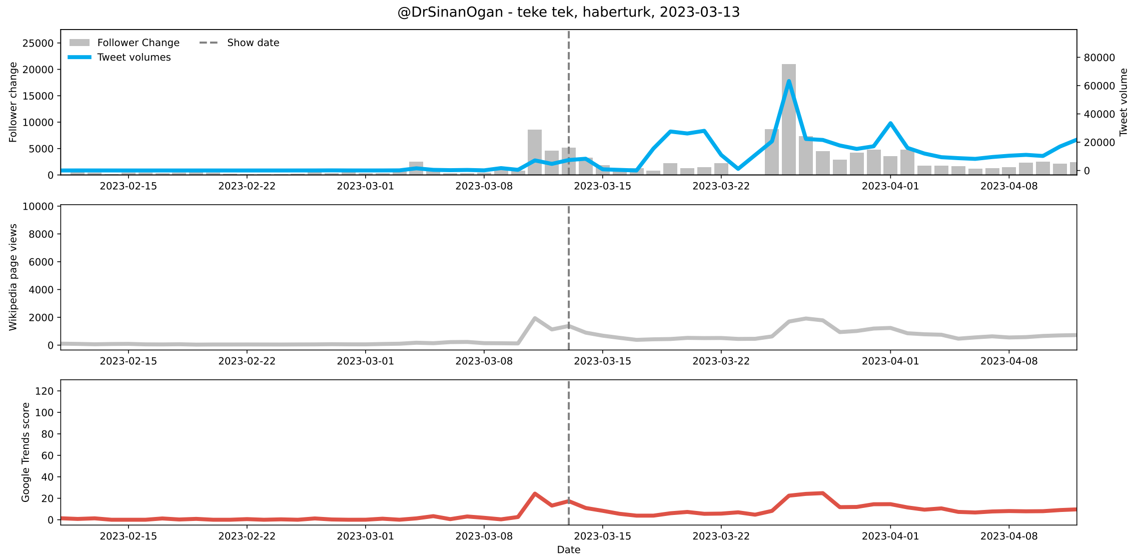

Figure A.12 Effect of participating the Habertürk show “Teke Tek”, Sinan Ogan .

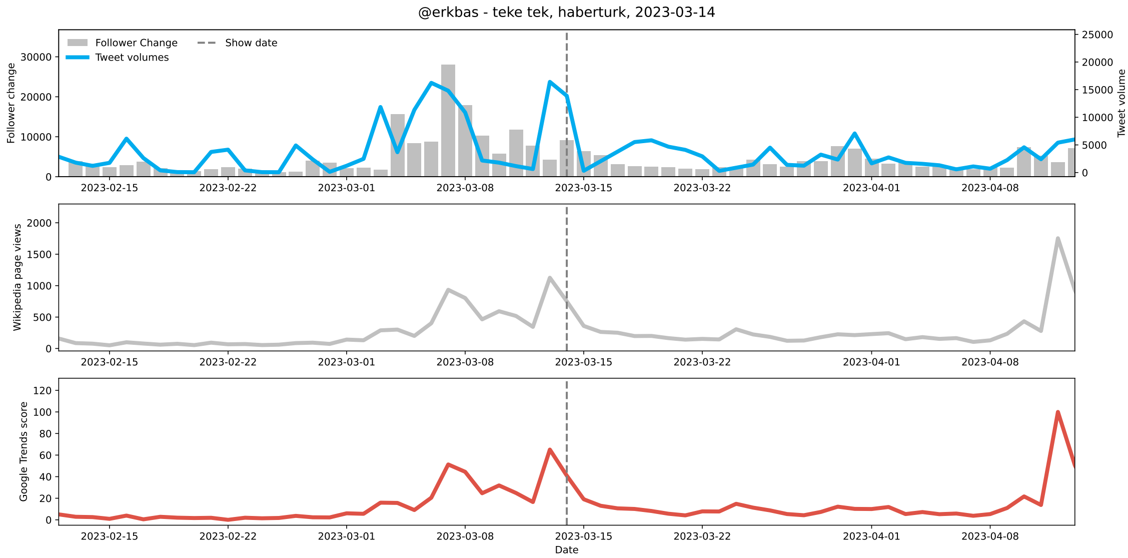

Figure A.13 Effect of participating the Habertürk show “Teke Tek”, Erkan Baş .

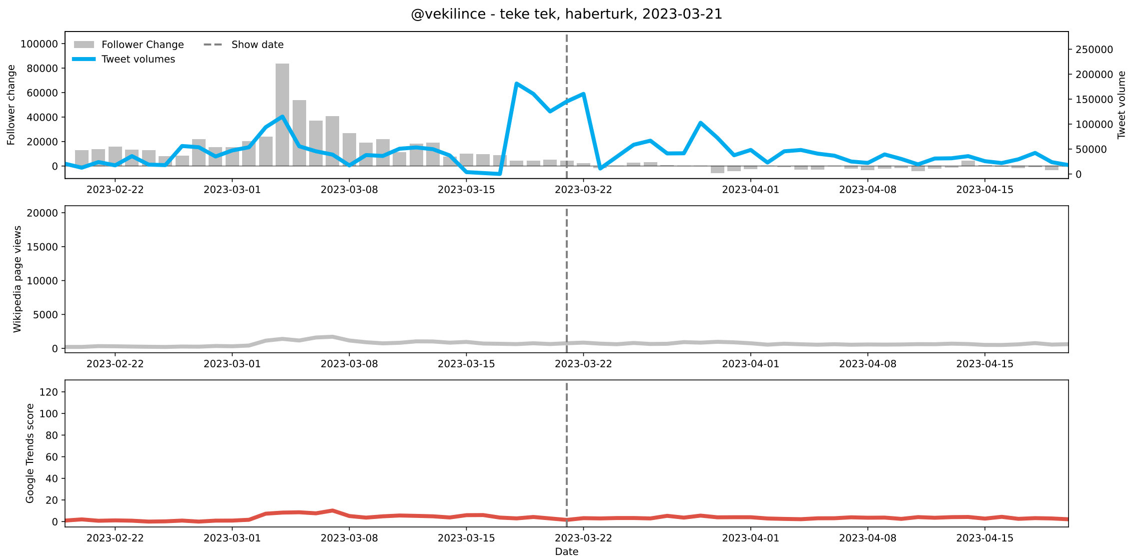

Figure A.14 Effect of participating the Habertürk show “Teke Tek”, Muharrem İnce
.

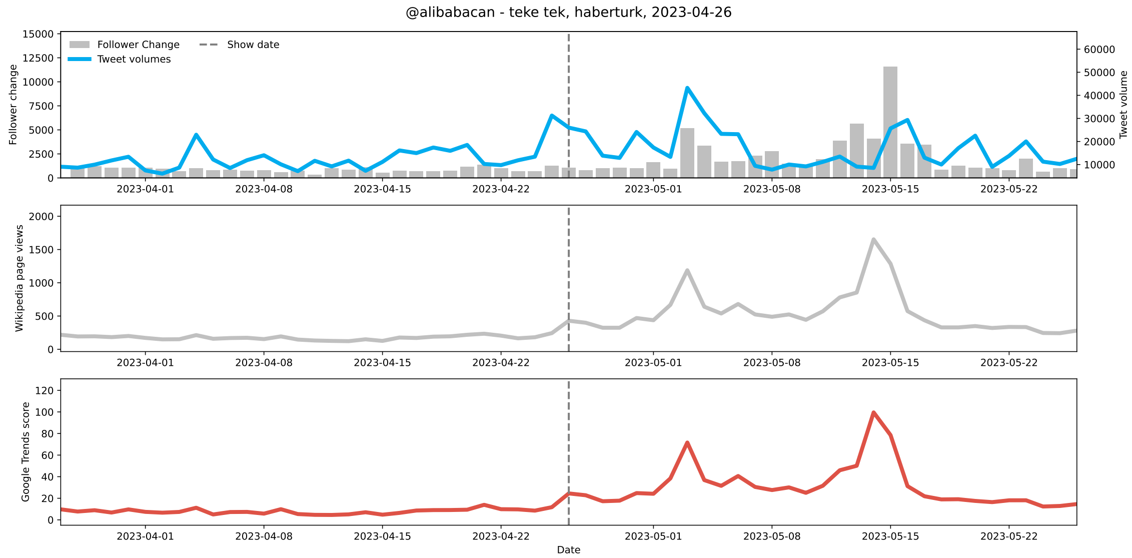

Figure A.15 Effect of participating the Habertürk show “Teke Tek”, Ali Babacan .

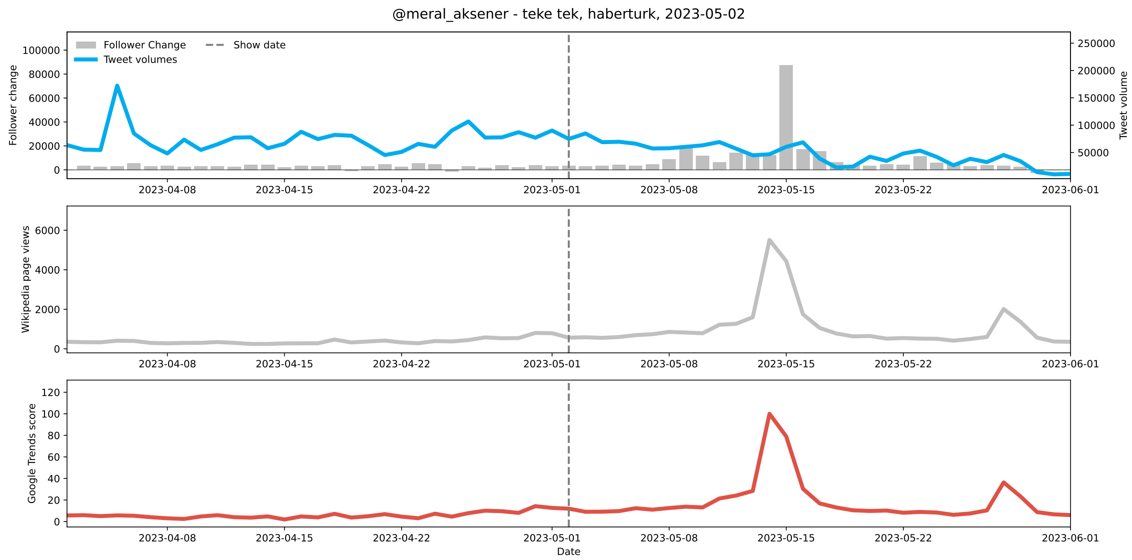

Figure A.16 Effect of participating the Habertürk show “Teke Tek”, Meral Akşener .

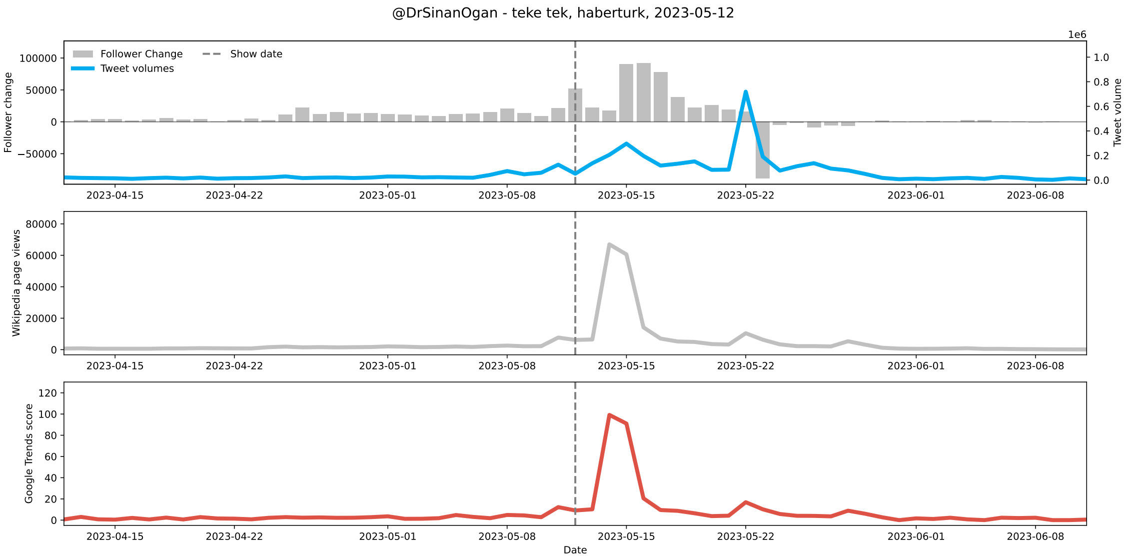

Figure A.17 Effect of participating the Habertürk show “Teke Tek”, Sinan Ogan .

TV100 - Uğur Dündar ile Haftanın Panoraması

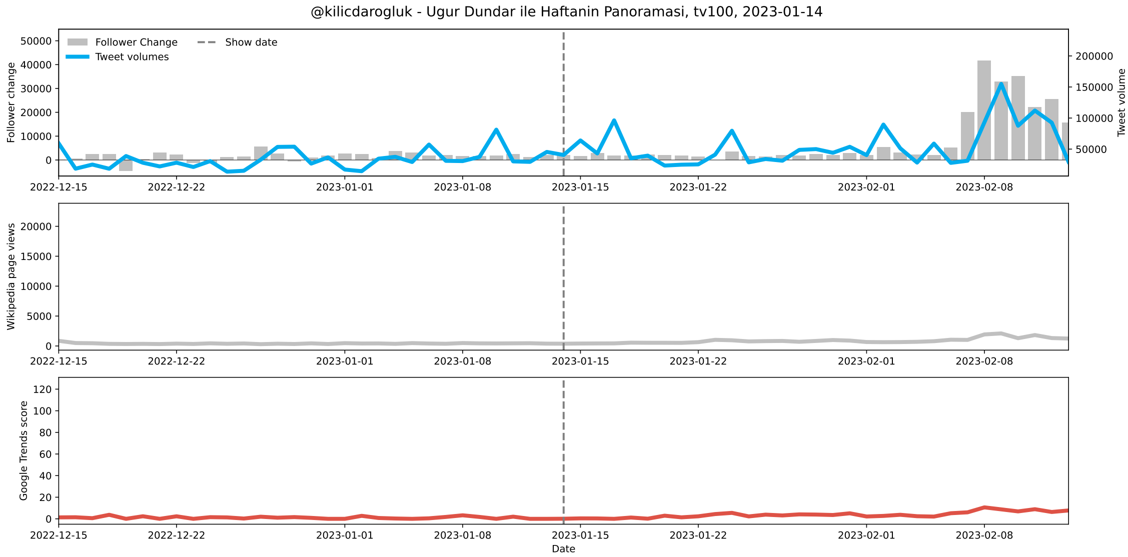

Figure A.18 Effect of participating the TV100 show “Uğur Dündar ile Haftanın Panoraması”, Kemal Kılıçdaroğlu .

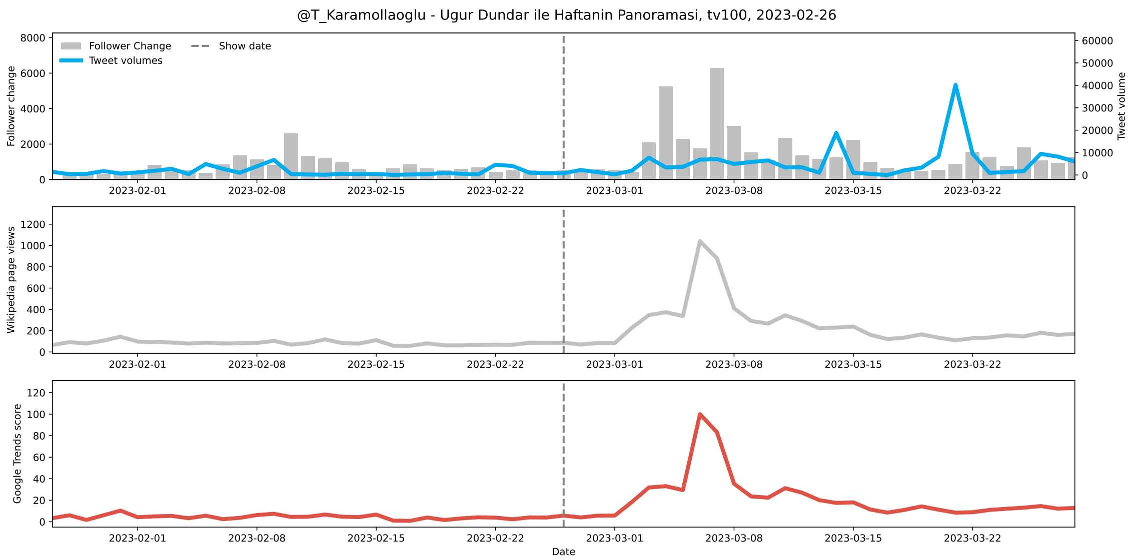

Figure A.19 Effect of participating the TV100 show “Uğur Dündar ile Haftanın Panoraması”, Temel Karamollaoğlu .

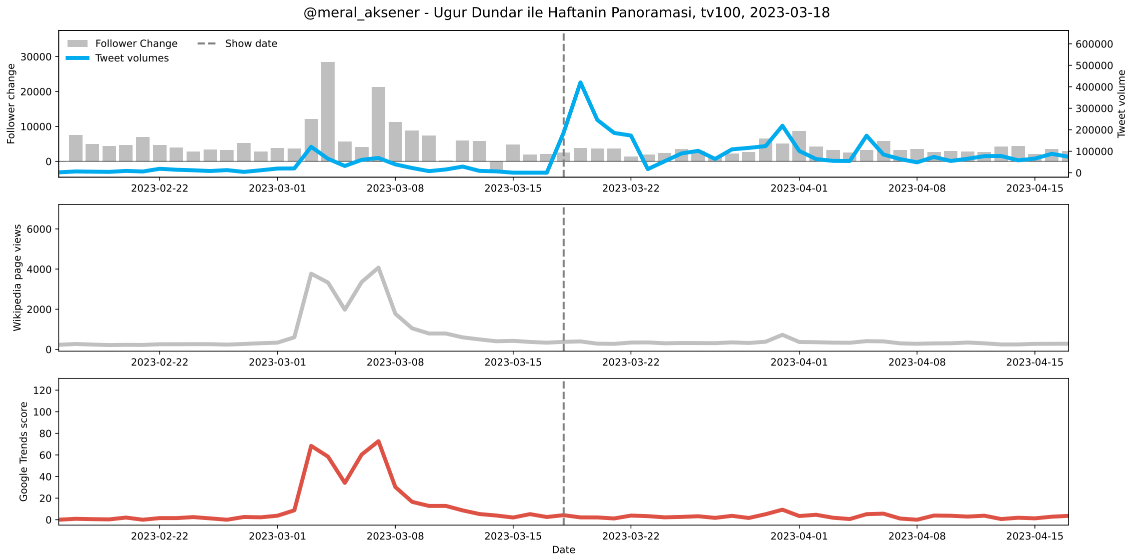

Figure A.20 Effect of participating the TV100 show "Uğur Dündar ile Haftanın Panoraması", Meral Akşener .

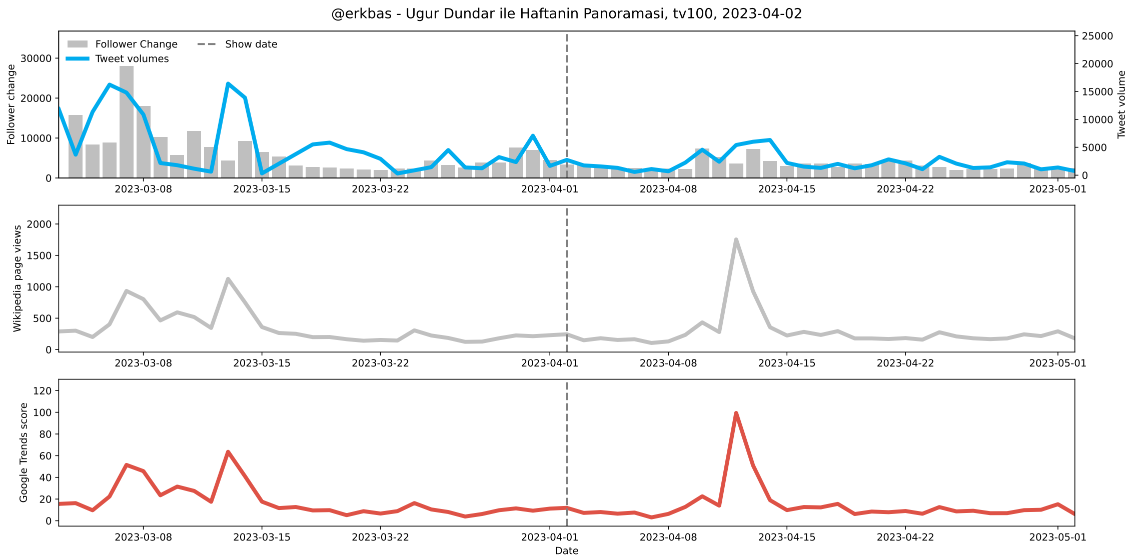

Figure A.21 Effect of participating the TV100 show "Uğur Dündar ile Haftanın Panoraması", Erkan Baş .

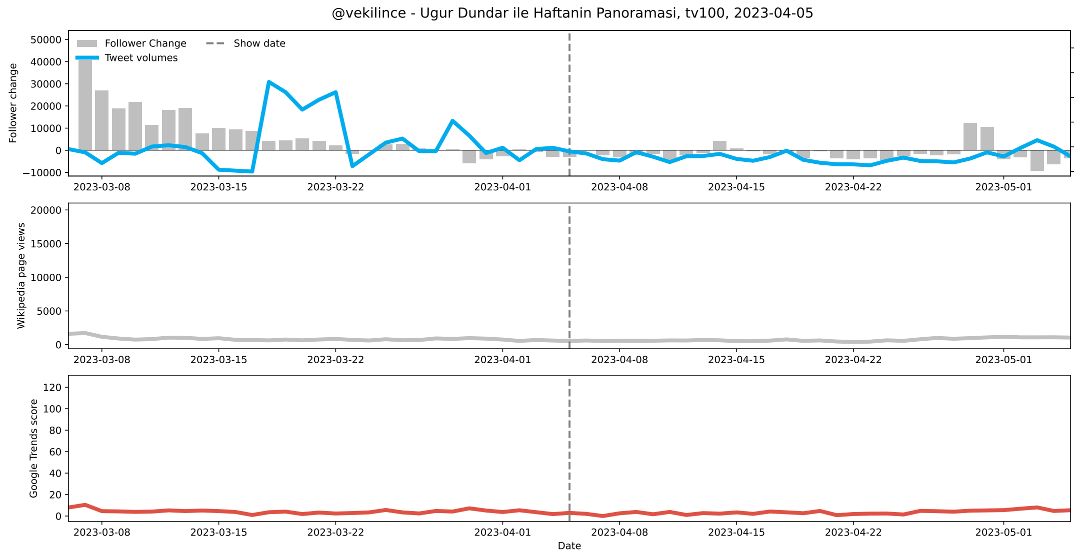

Figure A.22 Effect of participating the TV100 show “Uğur Dündar ile Haftanın Panoraması”, Muharrem İnce .

Sözcü - Liderler Özel

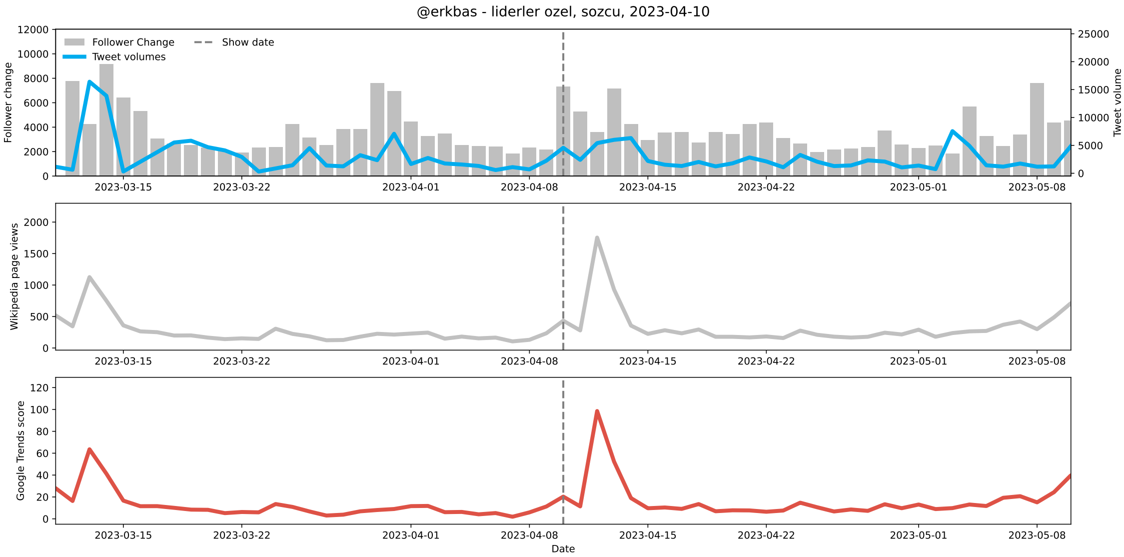

Figure A.23 Effect of participating the Sözcü show “Liderler Özel”, Erkan Baş .

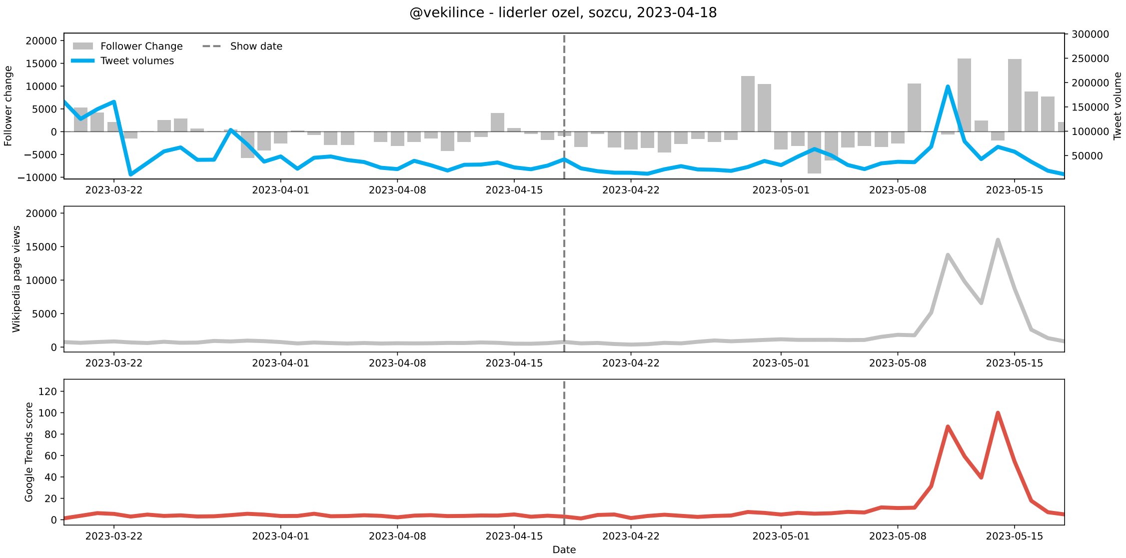

Figure A.24 Effect of participating the Sözcü show “Liderler Özel”, Muharrem İnce .

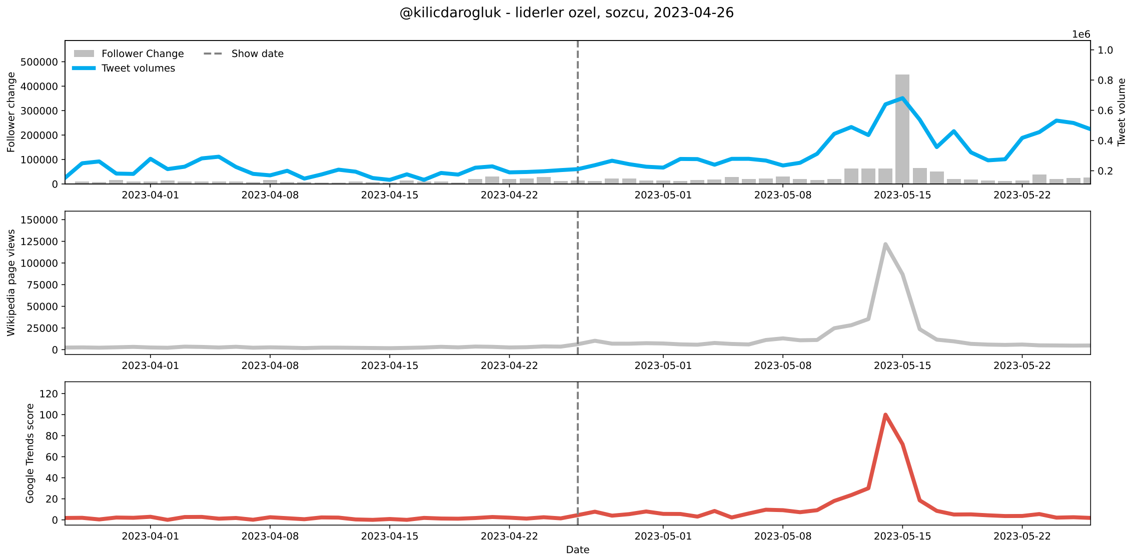

Figure A.25 Effect of participating the Sözcü show “Liderler Özel”, Kemal Kılıçdaroğlu .

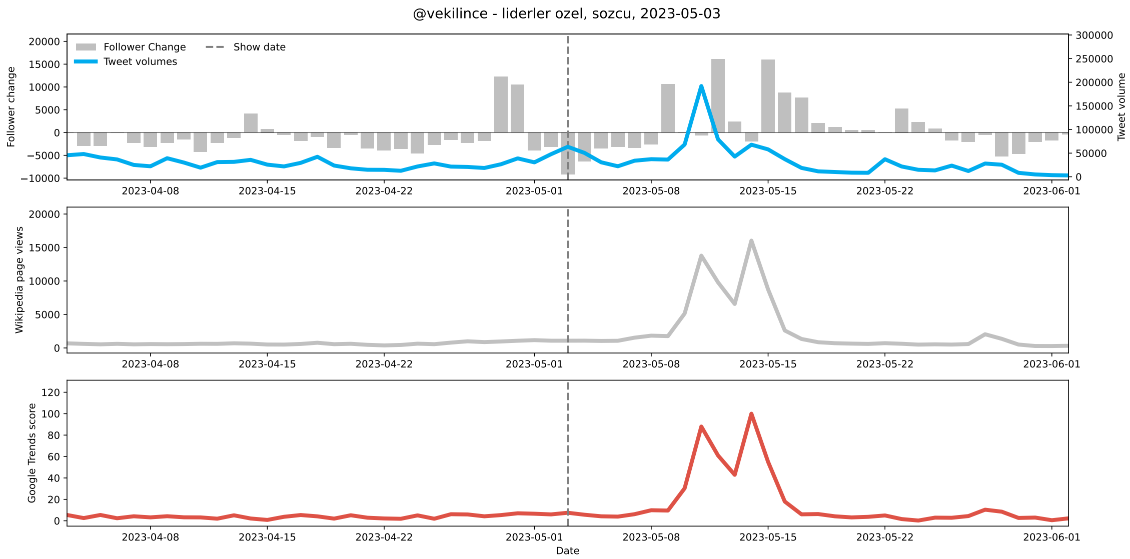

Figure A.26 Effect of participating the Sözcü show “Liderler Özel”, Muharrem İnce .

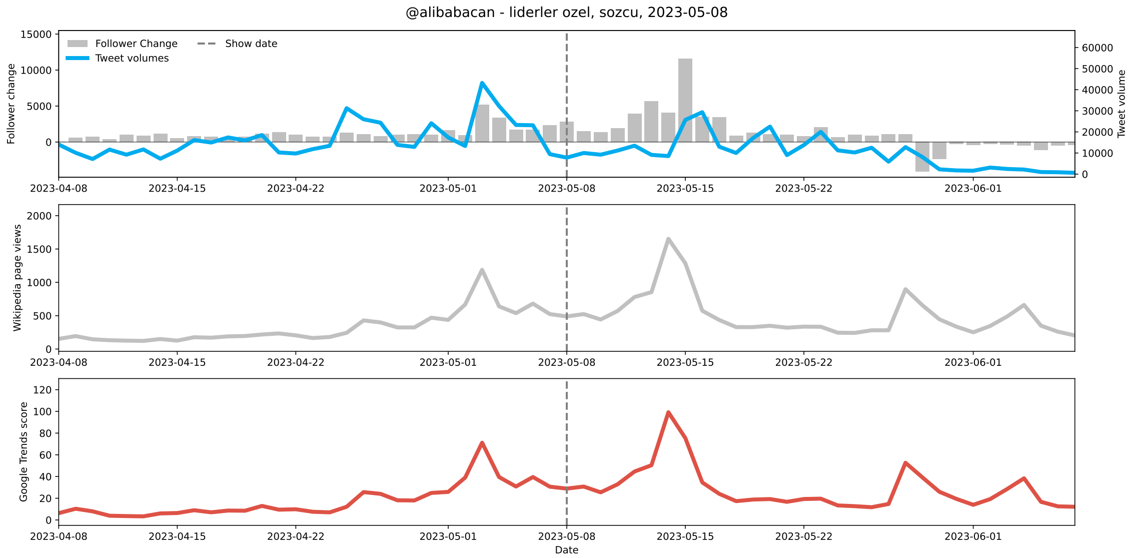

Figure A.27 Effect of participating the Sözcü show “Liderler Özel”, Ali Babacan .

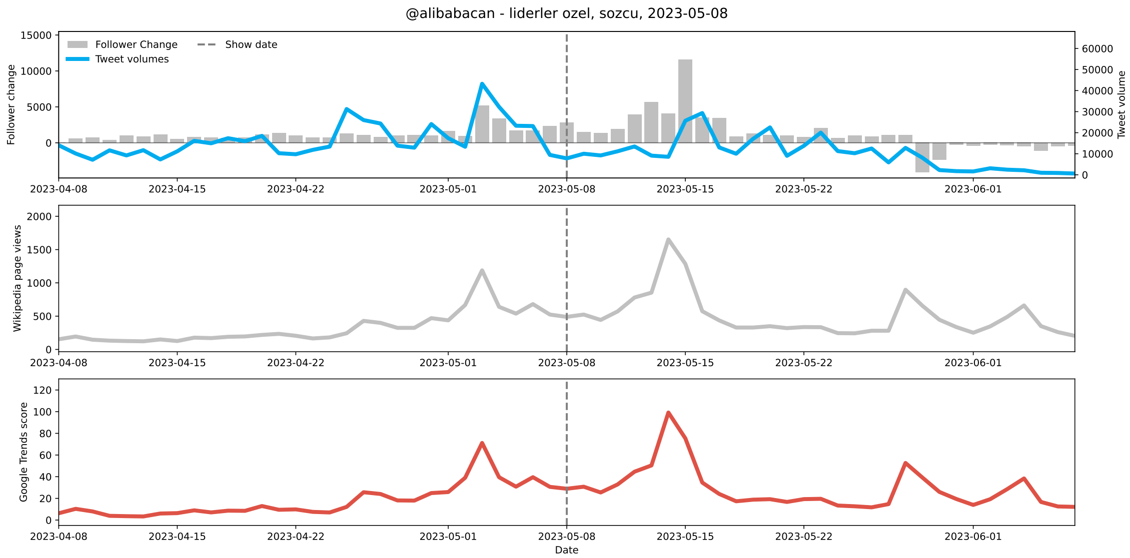

Figure A.28 Effect of participating the Sözcü show “Liderler Özel”, Ali Babacan .

NOW Haber - Liderler Fox'ta

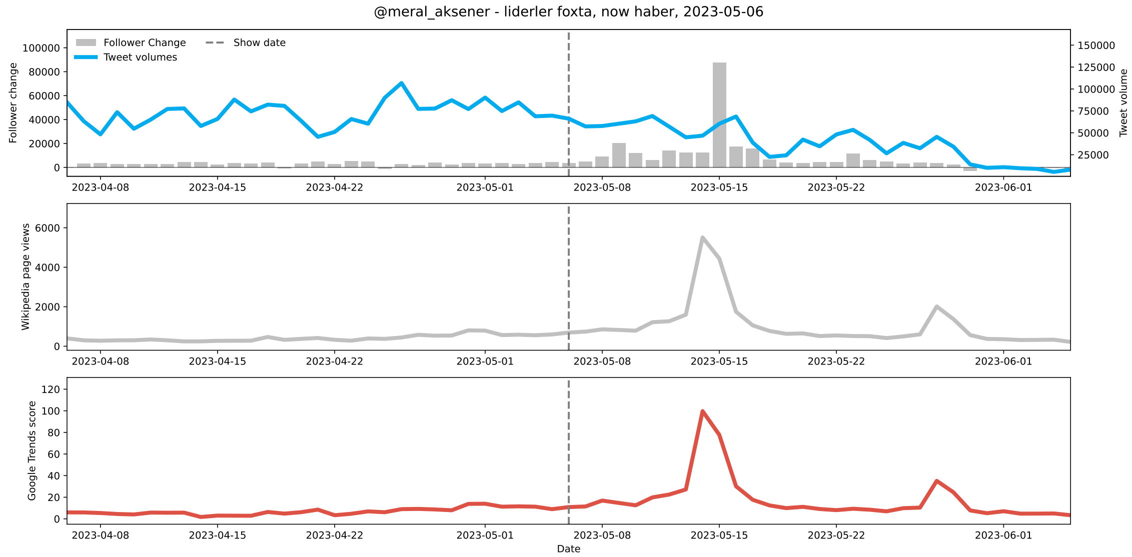

Figure A.29 Effect of participating the NOW HAber show “Liderler Fox'ta”, Meral Akşener .

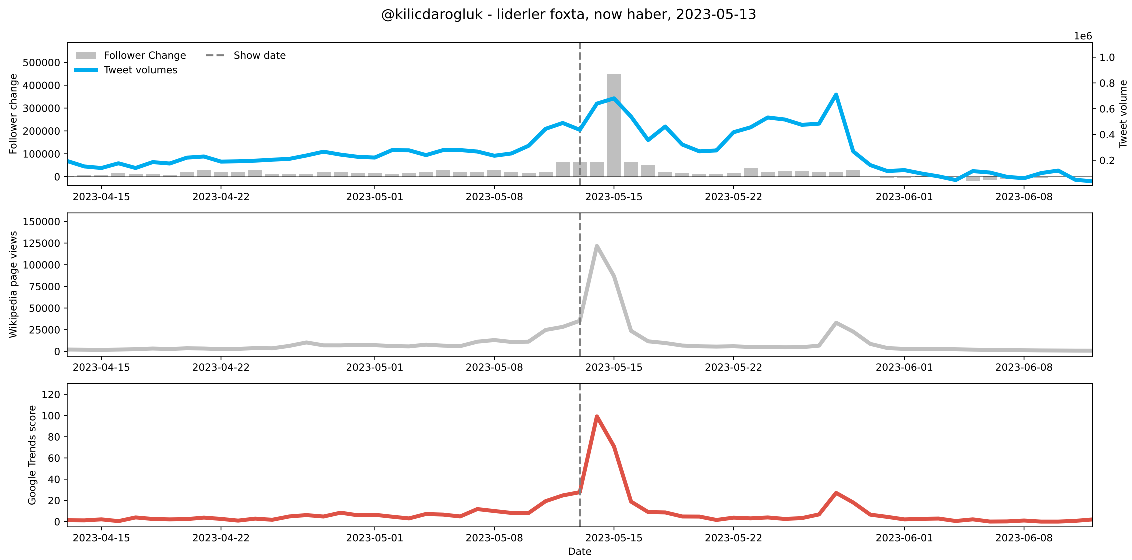

Figure A.30 Effect of participating the NOW HAber show “Liderler Fox'ta”, Kemal Kılıçdaroğlu .

Cumhurbaşkanı Özel Yayın

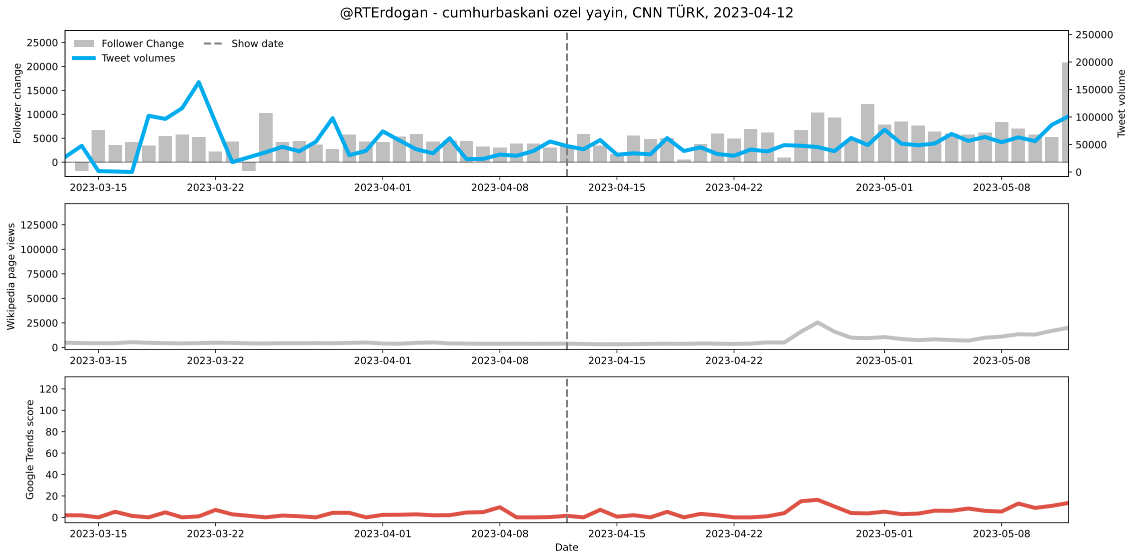

Figure A.31 Cumhurbaşkanı Özel Yayın .

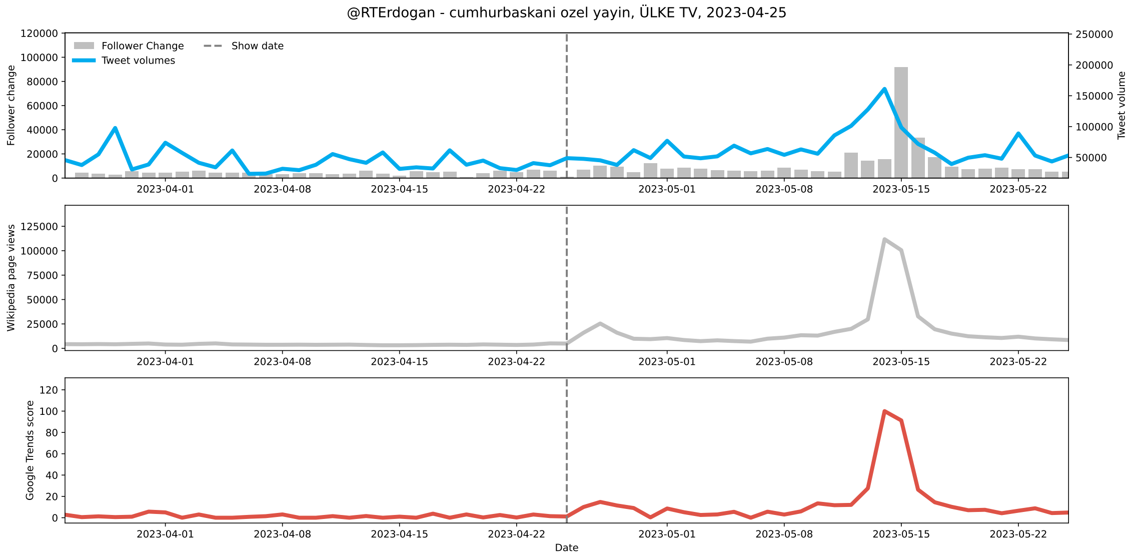

Figure A.32 Cumhurbaşkanı Özel Yayın .

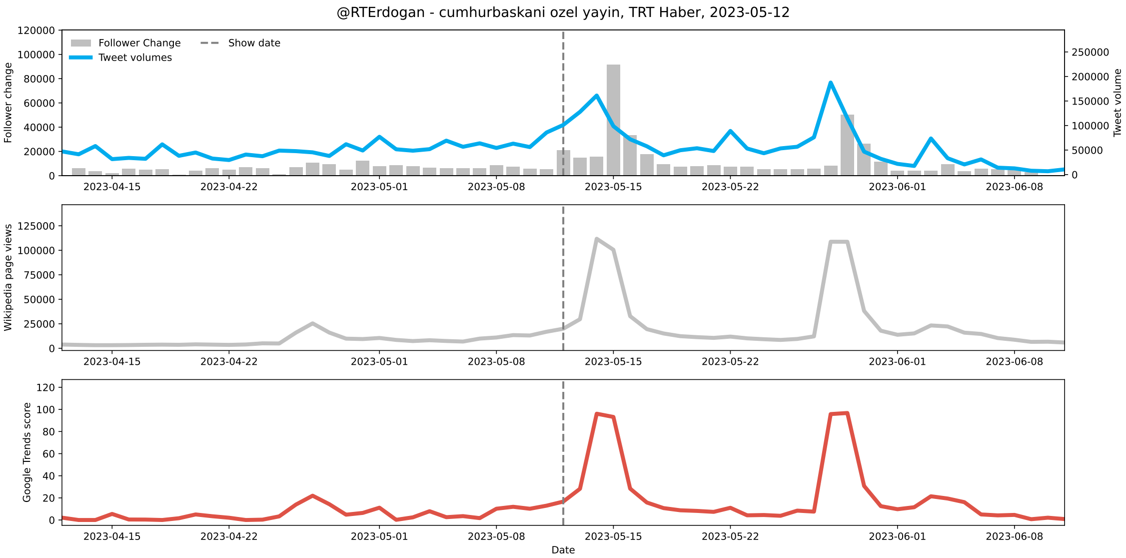

Figure A.33 Cumhurbaşkanı Özel Yayın .

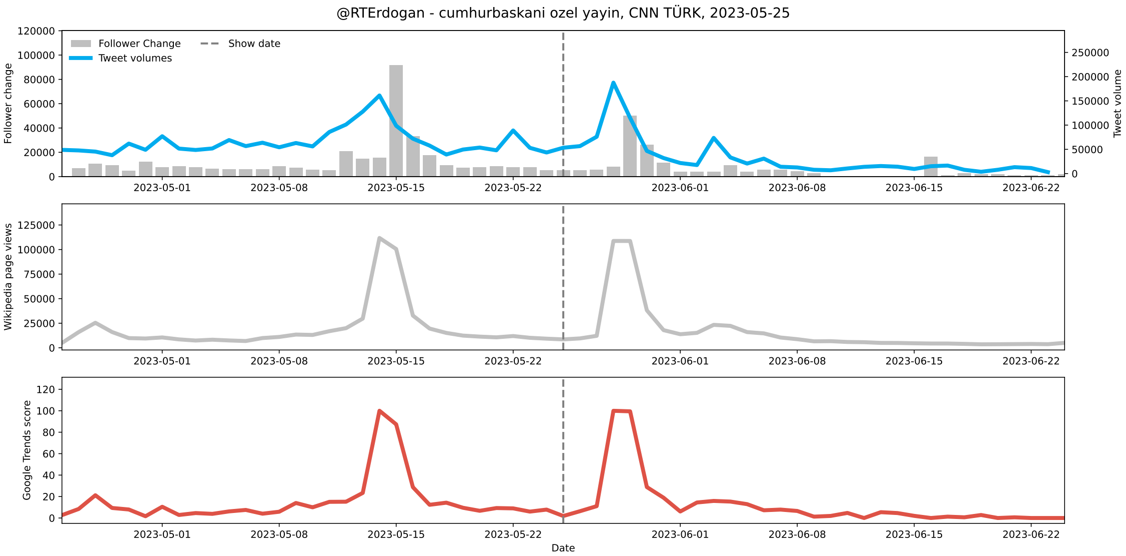

Figure A.34 Cumhurbaşkanı Özel Yayın .

Follower Compositions

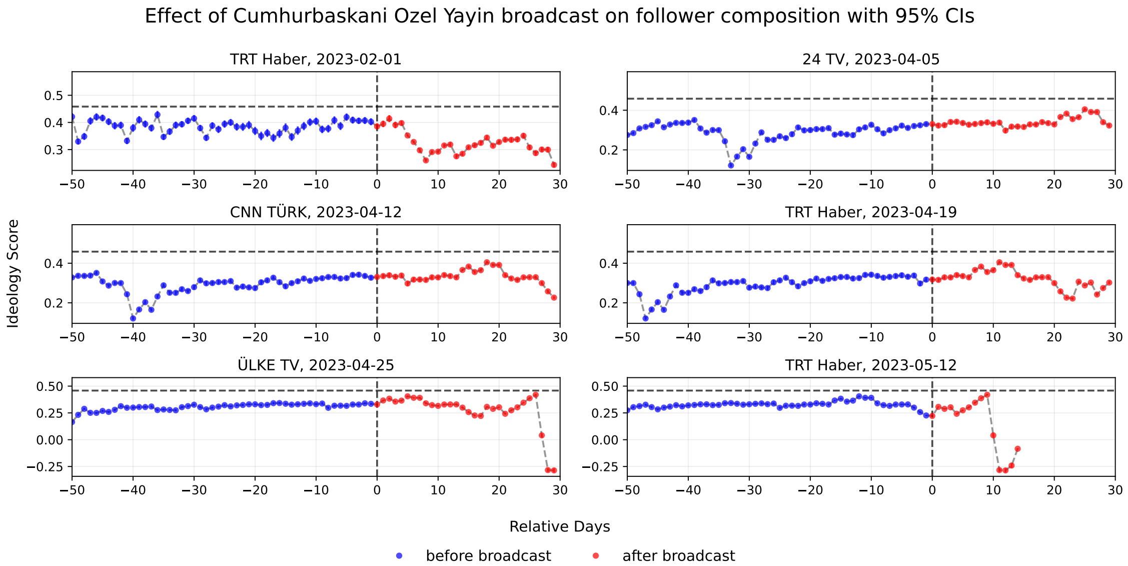

Figure A.35 Follower composition change before and after RTE appear on the Cumhurbaşkanı Özel Yayın. The graph shows the average daily ideology scores of new followers around show date. Horizontal line represents participant's estimated ideology scores. Vertical line shows the broadcast date.

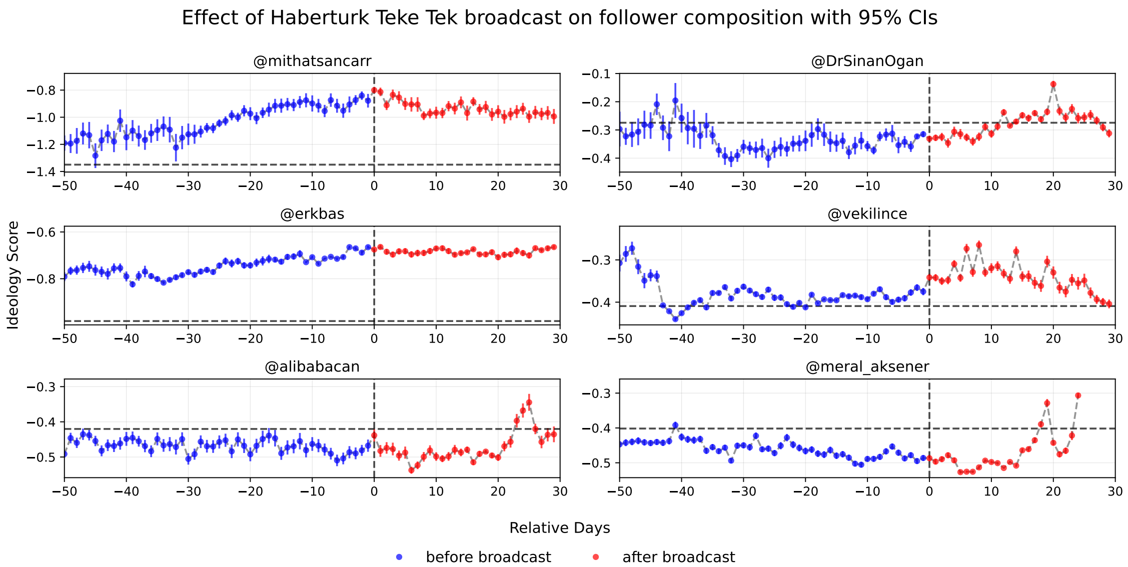

Figure A.36 Follower composition change before and after guest politicians appear on the Habertürk - Teke Tek. The graph shows the average daily ideology scores of new followers around show date. Horizontal line represents participant's estimated ideology scores. Vertical line shows the broadcast date.

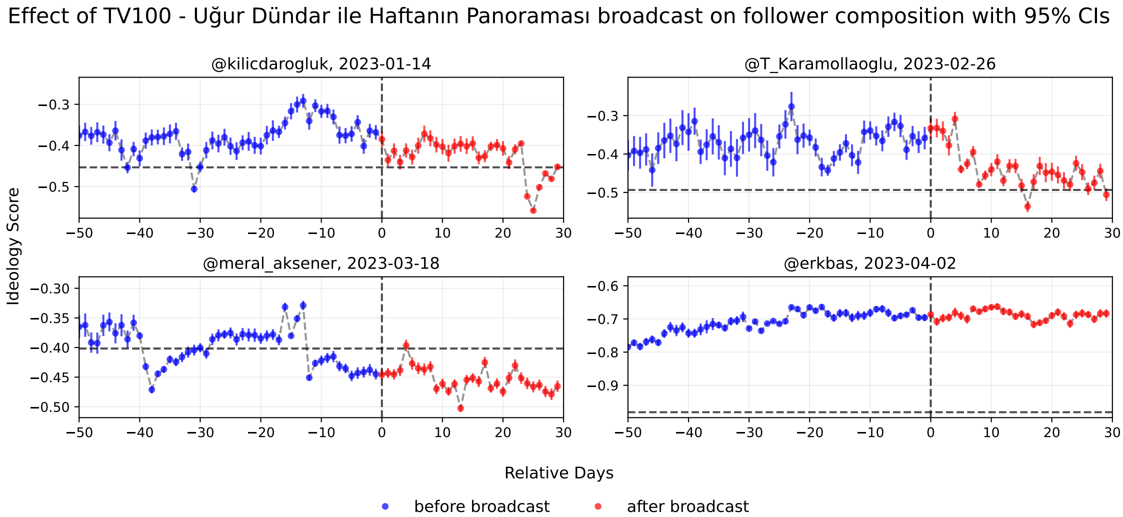

Figure A.37 Follower composition change before and after guest politicians appear on the TV100 - Uğur Dündar ile Haftanın Panoraması. The graph shows the average daily ideology scores of new followers around show date. Horizontal line represents participant's estimated ideology scores. Vertical line shows the broadcast date.

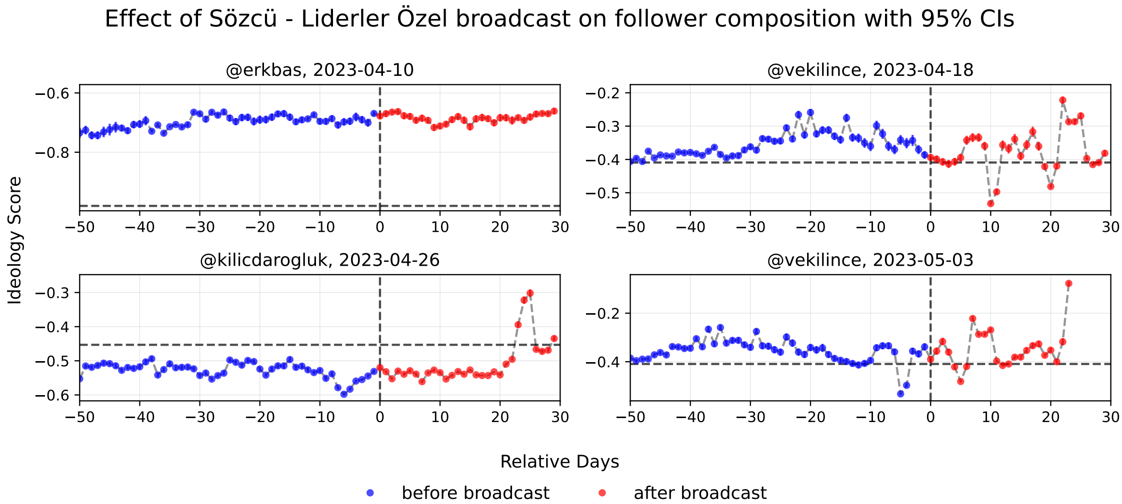

Figure A.38 Follower composition change before and after guest politicians appear on the Sözcü - Liderler Özel. The graph shows the average daily ideology scores of new followers around show date. Horizontal line represents participant's estimated ideology scores. Vertical line shows the broadcast date.

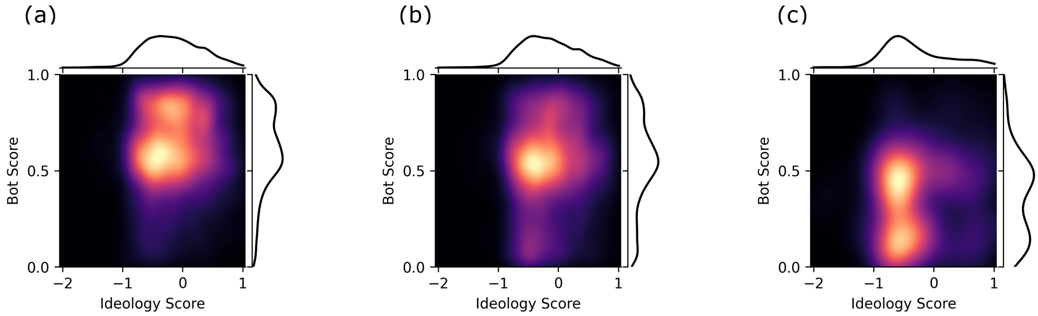

Figure A.39 Joint distribution, Ahmet Davutoglu.

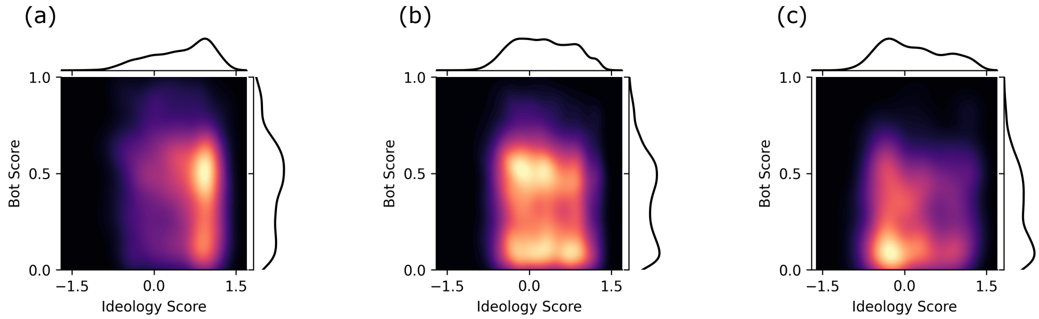

Figure A.40 Joint distribution, Metin Kulunk.

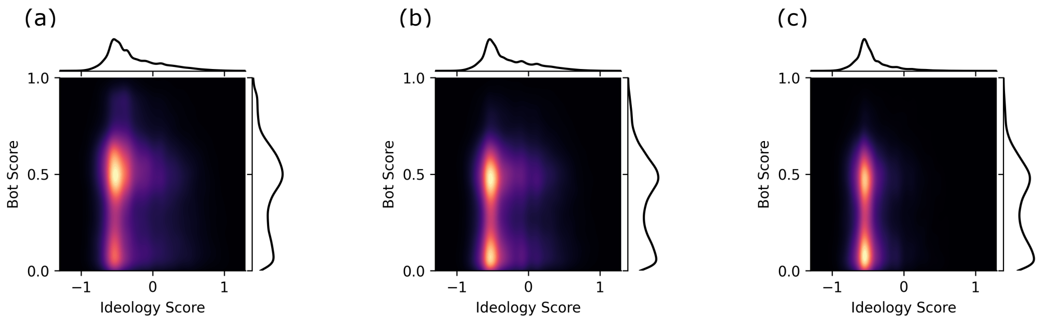

Figure A.41 Joint distribution, Sinan Ogan.

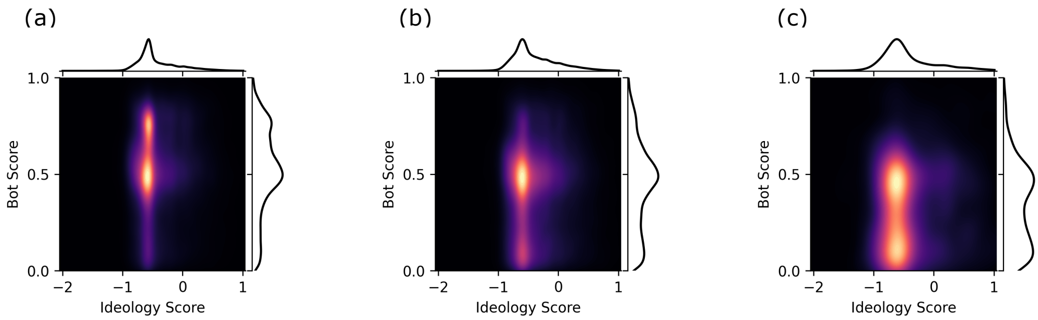

Figure A.42 Joint distribution, Umit Ozdag.

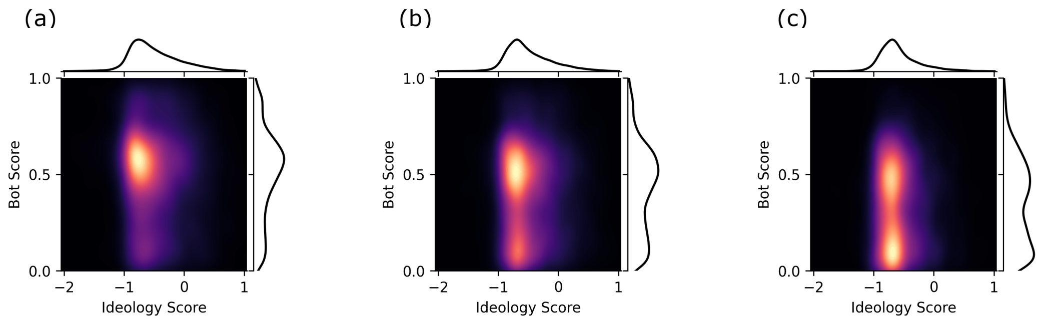

Figure A.43 Joint distribution, Abdullatif Sener.

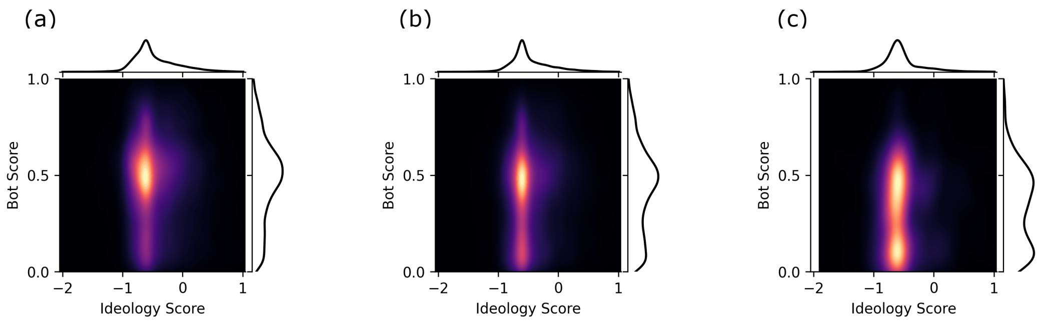

Figure A.44 Joint distribution, Cem Uzan.

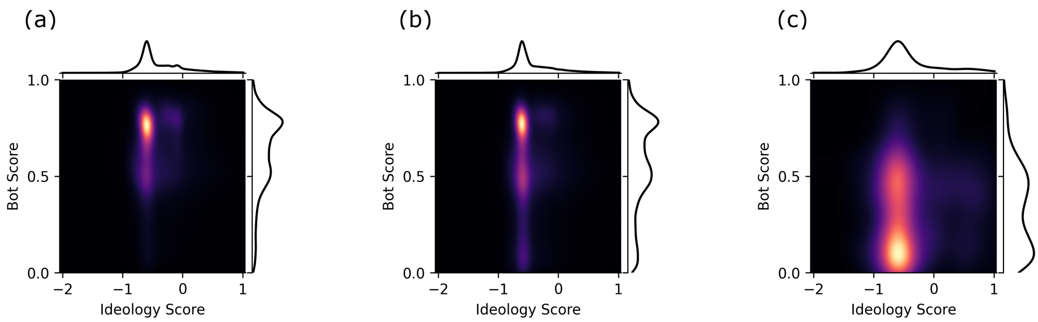

Figure A.45 Joint distribution, Muharrem Ince-1.

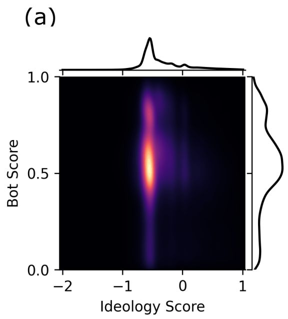

Figure A.46 Joint distribution, Muharrem Ince-2.

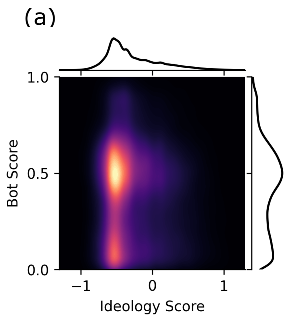

Figure A.47 Joint distribution, Sinan Ogan.

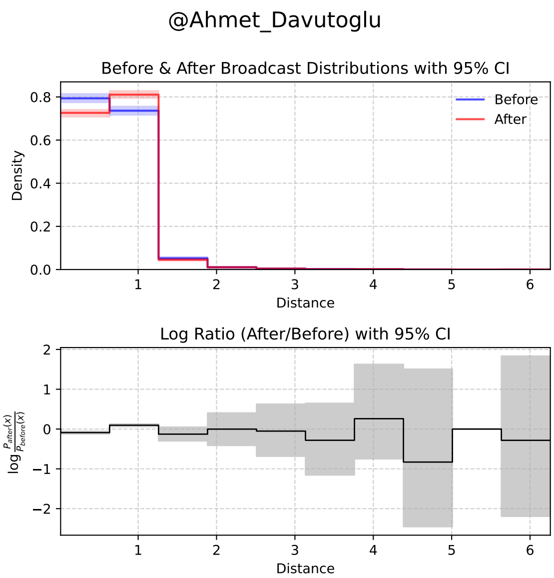

Figure A.48 Top panel: Step-histograms of absolute distances for the new followers of Ahmet Davutoglu during the 15 days before (blue) and after (red) his broadcast appearance, with 95% bootstrap confidence bands shaded around each curve. Bottom panel: Log density ratio across the distances with 95% confidence intervals (gray).

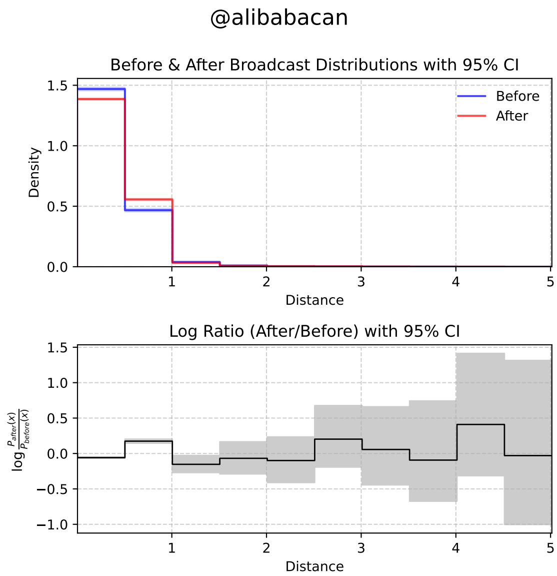

Figure A.49 Top panel: Step-histograms of absolute distances for the new followers of Ali Babacan during the 15 days before (blue) and after (red) his broadcast appearance, with 95% bootstrap confidence bands shaded around each curve. Bottom panel: Log density ratio across the distances with 95% confidence intervals (gray).

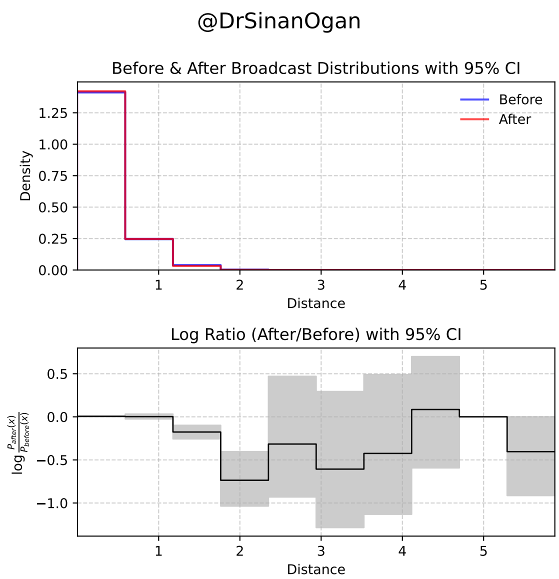

Figure A.50 Top panel: Step-histograms of absolute distances for the new followers of Sinan Ogan during the 15 days before (blue) and after (red) his broadcast appearance, with 95% bootstrap confidence bands shaded around each curve. Bottom panel: Log density ratio across the distances with 95% confidence intervals (gray).

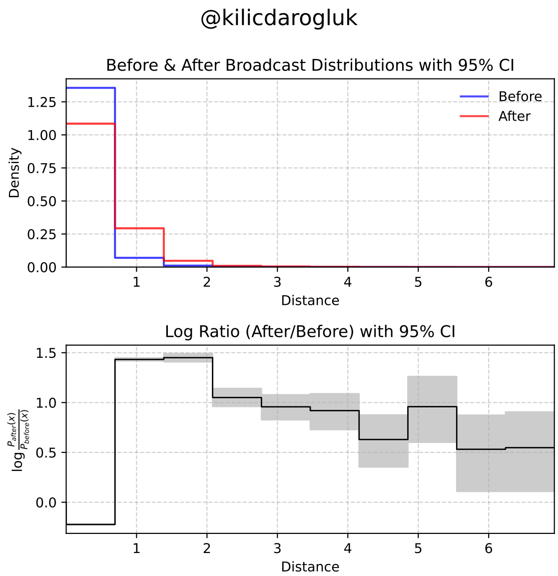

Figure A.51 Top panel: Step-histograms of absolute distances for the new followers of Kemal Kılıçdaroğlu during the 15 days before (blue) and after (red) his broadcast appearance, with 95% bootstrap confidence bands shaded around each curve. Bottom panel: Log density ratio across the distances with 95% confidence intervals (gray).

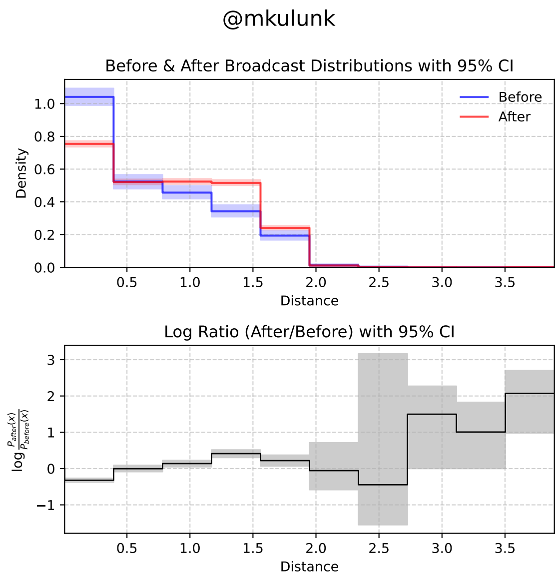

Figure A.52 Top panel: Step-histograms of absolute distances for the new followers of Metin Külünk during the 15 days before (blue) and after (red) his broadcast appearance, with 95% bootstrap confidence bands shaded around each curve. Bottom panel: Log density ratio across the distances with 95% confidence intervals (gray).

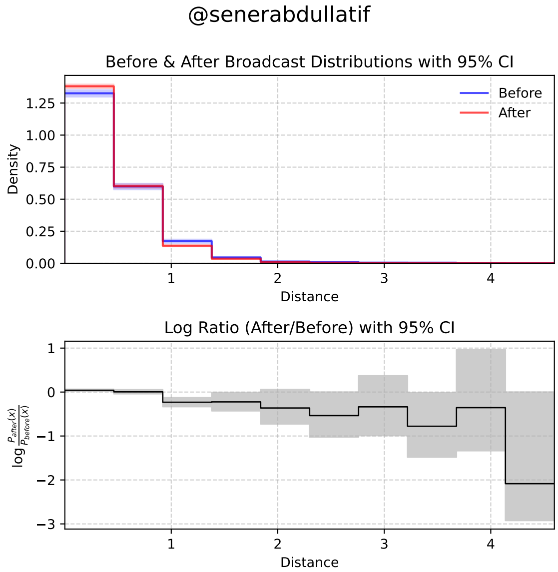

Figure A.53 Top panel: Step-histograms of absolute distances for the new followers of Abdullatif Şener during the 15 days before (blue) and after (red) his broadcast appearance, with 95% bootstrap confidence bands shaded around each curve. Bottom panel: Log density ratio across the distances with 95% confidence intervals (gray).

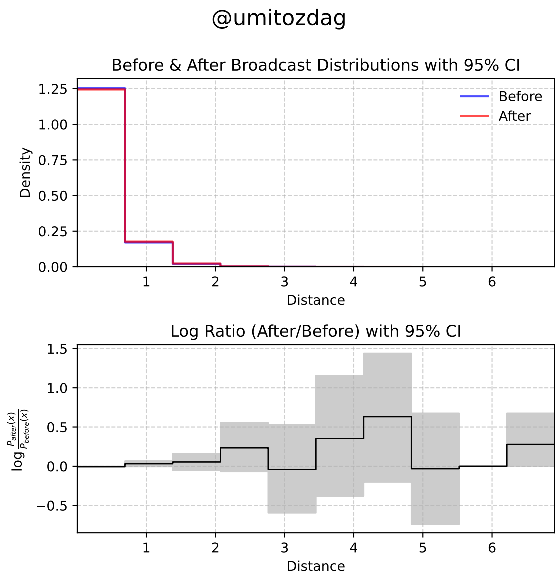

Figure A.54 Top panel: Step-histograms of absolute distances for the new followers of Ümit Özdağ during the 15 days before (blue) and after (red) his broadcast appearance, with 95% bootstrap confidence bands shaded around each curve. Bottom panel: Log density ratio across the distances with 95% confidence intervals (gray).

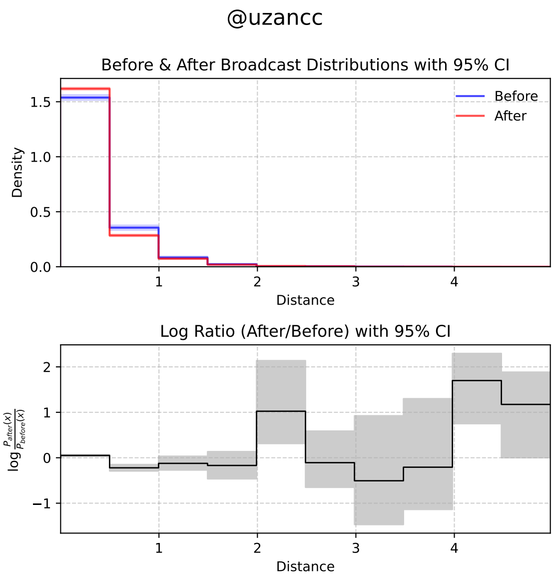

Figure A.55 Top panel: Step-histograms of absolute distances for the new followers of Cem Uzan during the 15 days before (blue) and after (red) his broadcast appearance, with 95% bootstrap confidence bands shaded around each curve. Bottom panel: Log density ratio across the distances with 95% confidence intervals (gray).

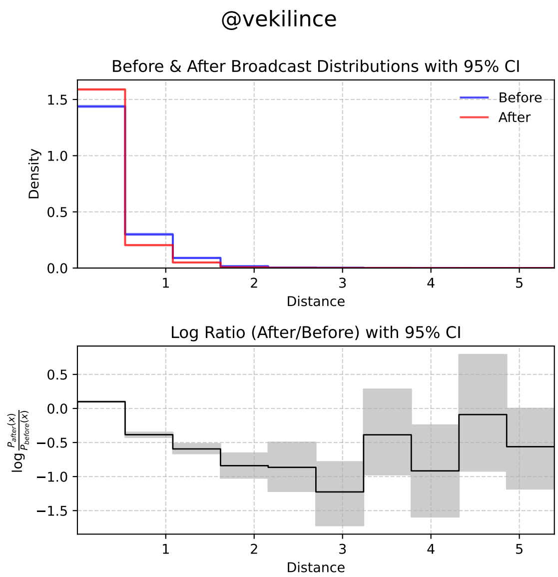

Figure A.56 Top panel: Step-histograms of absolute distances for the new followers of Muharrem İnce during the 15 days before (blue) and after (red) his broadcast appearance, with 95% bootstrap confidence bands shaded around each curve. Bottom panel: Log density ratio across the distances with 95% confidence intervals (gray).

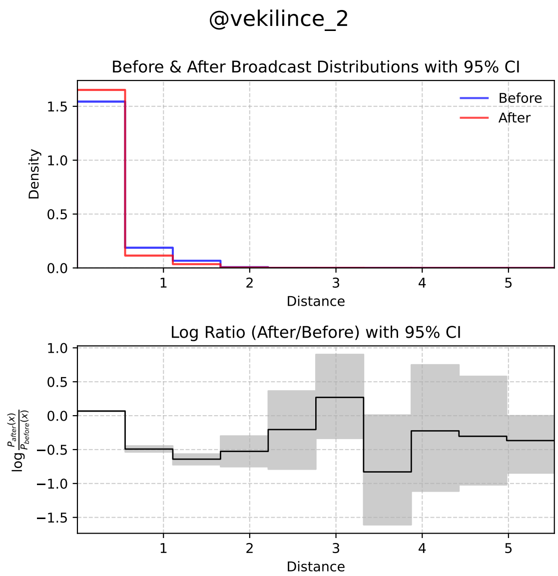

Figure A.57 Top panel: Step-histograms of absolute distances for the new followers of Muharrem Ince's second appearance during the 15 days before (blue) and after (red) his broadcast appearance, with 95% bootstrap confidence bands shaded around each curve. Bottom panel: Log density ratio across the distances with 95% confidence intervals (gray).

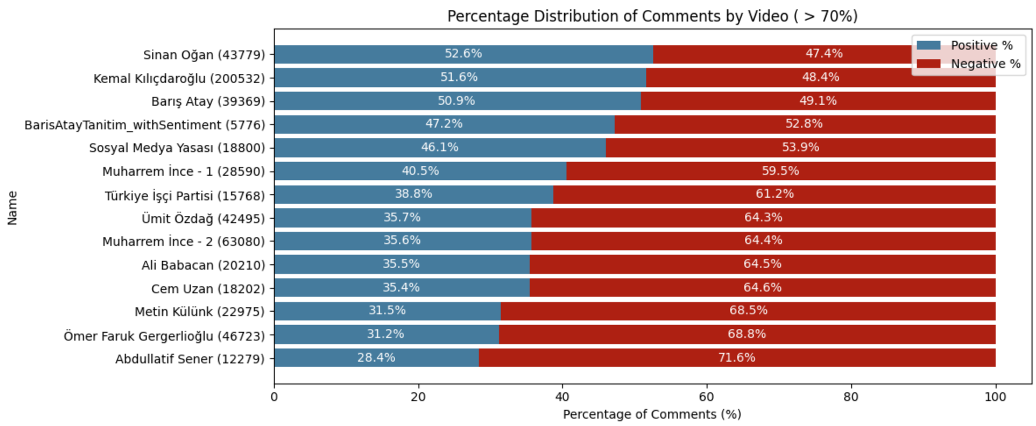

Figure A.58 Percentage distributions of comments by sentiment for Mevzular Acik Mikrofon participants.